A NOVEL FRAMEWORK FOR SOFTWARE CLONE DETECTION USING ADAPTIVE PREFIX FILTERING

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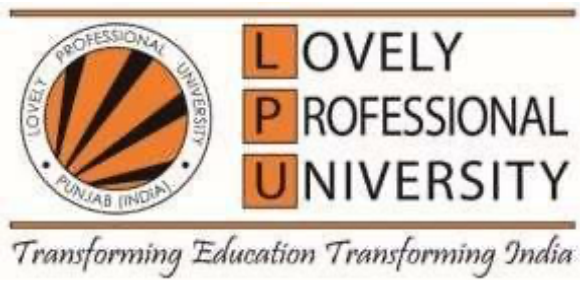

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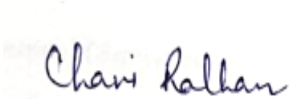
DECLARATION

I, hereby declare that the presented work in the thesis entitled "A Novel Framework for Software Clone Detection Using Adaptive Prefix Filtering" in fulfillment of my degree of **Doctor of Philosophy (Ph.D.)** is the outcome of research work carried out by me under the supervision Dr. Navneet Malik, working as **Associate Professor** in the Computer Science & Engineering of Lovely Professional University, Punjab, India. In keeping with the general practice of reporting scientific observations, due acknowledgments have been made whenever the work described here has been based on the findings of other investigators. This work has not been submitted in part or full to any other University or Institute for the award of any degree.



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CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled "A Novel Framework for Software Clone Detection Using Adaptive Prefix Filtering" submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in the Computer Science & Engineering, is a research work carried out by Chavi Ralhan, Registration No. 41900220 is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

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Name of supervisor: Dr. Navneet Malik

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ABSTRACT

In this research work, we have conducted an explorative study on the challenges of code clones, covering all types of code clone types. Our investigation revealed that there is no single standard method in the industry for detecting code clones, with most recent work being combinational and hybrid. This trend is due to the varying critical factors in different scenarios: sometimes fine-grain analysis is crucial, in other cases syntax capture is vital, occasionally the hierarchy of the code listing is critical, and in some instances, visual inspection is necessary.

After conducting comparative studies in contemporary literature, we identified a need to leverage methods such as Abstract Syntax Trees (AST) to capture each fragment of the code structure and compute metrics that can detect clone progression across code repositories. To evaluate our approach, we implemented a multi-layer meta-classifier (custom) system.

The performance of this system was assessed using a confusion matrix and all other performance metrics such as recall precision etc., yielding an overall accuracy of 92.13%. Class-wise analysis showed high recall and precision across all categories, with values consistently above 90%, indicating robust performance in distinguishing between different clone types and non-clones.

To further investigate the efficacy of ensemble learning approaches in code clone detection, we conducted a comprehensive analysis of various meta-classifier architectures. This analysis yielded significant insights into the performance characteristics of different configurations:

1. Architectural Performance

- Configurations 'A, B, C, E' and 'A, B, DE' showed superior precision for non-clone code identification.
- The 'D, A, B' configuration excelled in precision for code clone detection.
- A general trend of higher precision values for clone detection was observed across architectures.

2. **Precision-Recall Trade-offs**

- Clear trade-offs between precision and recall were evident across different architectural configurations.
- The 'C, D, A' architecture emerged as a notable performer, achieving a commendable balance between precision and recall for both clone and non-clone classes

3. **Individual Classifier Contributions**

- Random Forest Classifier (A) effectively mitigated overfitting.
- Decision Tree prop (B) added interpretability to the model.
- Gradient Boosting (C) enhanced overall predictive power.
- Logistic Regression (D) provided a stable baseline and improved linear separability handling.

4. **Meta-Classifier Efficacy**

The meta-classifier achieved a balanced performance with a recall of 98.75% and a precision of 90.99%, outperforming individual boosting algorithms and accuracy above 90%. This balance suggests adeptness at both identifying a substantial portion of cloned instances and minimizing false positives.

Our findings contribute to the field of code clone detection by proposing a hybrid, metrics-driven approach that demonstrates high accuracy across diverse clone types. The slightly lower performance in detecting Type-2 clones suggests areas for future improvement, while the superior performance in identifying semantic clones highlights the strength of our method.

The meta-classifier balanced performance positions it as a robust solution for real-world software development environments, addressing the need for efficient code review processes and effective management of code quality and maintainability.

This study demonstrates the potential of advanced machine learning techniques,

particularly ensemble methods, and meta-learning approaches, in significantly improving the accuracy and reliability of code clone detection. The developed meta-classifier represents a significant step forward in addressing the challenges of code duplication in large-scale software projects.

As software systems continue to grow in complexity and scale, such sophisticated clone detection tools will play an increasingly crucial role in maintaining code quality, enhancing software maintainability, and improving the efficiency of software development processes. This research not only contributes to the theoretical understanding of applying machine learning to software engineering problems but also offers practical tools and insights for developers and organizations striving to manage and improve their codebases effectively.

This research paves the way for more adaptive and nuanced code clone detection techniques, addressing the complex challenges posed by evolving software development practices.

PREFACE/ACKNOWLEDGEMENT

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INTRODUCTION

Code clone detection is a well-studied problem in software engineering, and researchers have developed various techniques to address it [1] [2]. Before, we take a deep dive into this domain. Here is the background, concepts, and terms that are used in understanding the landscape of this problem.

In terms of the definition, code clones basically refer to segments or parts of code that are identical or similar to each other in all respects [3] [4]. These clones can emerge due to various reasons, such as copy-pasting code with slight alterations, reusing code patterns, or implementing similar functionalities (overloading and overriding) in different parts of a program to implement polymorphism [5] [6]. While cloning can sometimes expedite development cycles, it often leads to increased maintenance overhead and higher susceptibility to human error, mistakes, bugs, and unintentional vulnerabilities [7] [8]. Identifying and managing these clones is therefore crucial for maintaining code quality and reducing technical debt [9] [10].

1.1 Types of Code Clones

Code clones can be broadly categorized into four types:

1. Type-1 Clones (Exact Clones) [11] [12]: Type-1 Clones (Exact Clones) are identical code segments except for variations in white space and comments. Detecting Type-1 clones is relatively straightforward since it involves simple string matching. For example:

```
- def calculate area(width, height):
-   "C alculates the area of a rectangle"""
-   return width * height
-
- def calculate_rectangle_area(length, breadth):
-   """ Calculates the area of a rectangle (redundant naming)"
-   return length * breadth
-
- These functions are identical except for variable and comment variations.
```

```
+ def calculate_area(width, height):
+     """Calculates the area of a rectangle."""
+     return width * height
+
+ def calculate_area(width, height):
+     # Calculates the area of a rectangle
+     return width * height
+
+ These functions are identical except for whitespace and comments.
+ No variable names or function names change, making them true Type-1
clones.
```

These functions are identical except for variable and comment variations.

2. **Type-2 Clones (Renamed Clones)** [13] [14]**:** These clones involve identical code segments where variable names, function names, or literals have been renamed. Type-2 clones are more challenging to detect than Type-1 because they require more sophisticated pattern matching that accounts for semantic equivalence despite syntactic differences.

```
def calculate_area(width, height):
  return width * height

def get_rectangle_size(base, altitude): # Renamed variables
  return base * altitude
```

This code achieves the same functionality but renames variables (width to base, height to altitude).

3. **Type-3 Clones (Near-Miss Clones)** [15] [16] **:** These are code segments that have been copied with modifications such as added, deleted, or altered statements. Detecting Type-3 clones is complex as it requires understanding the underlying logic and structure of the code to identify similarities despite significant alterations.

```
def calculate_area(width, height):
  return width * height
def get_rectangle_area(length, breadth):
  area = length * breadth # Added variable assignment
  return area
```

Here, the logic is identical but an extra statement (assigning the result to a variable) is added. Both functions calculate area but the Type 4 clone adds error handling for negative inputs.

4. **Type-4 Clones (Semantic Clones)** [17] [18]**:** These clones perform the same computation but are implemented using different syntactic structures. Detecting Type-4 clones is the most challenging because it involves deep

semantic analysis to determine that different code segments achieve the same functionality.

```
        def calculate_area(width, height):
  return width * height

def get_rectangle_area(length, breadth):
  if length > 0 and breadth > 0:
    return length * breadth
  else:
    return 0 # Handles negative inputs differently
```

Figure 1.1: Types of Clones

Research shows that the Type 4 clones are the most challenging to detect because they require understanding the deeper meaning (semantics) of the code. Simple string matching won't work as the code structure might be different. Hence, there is a need for

a clone detection tool that needs to analyse the code to identify that both achieve the same functionality despite syntactic variations.

1.2 Frequently Used Methods of Detection:

From experimentation and contemporary literature, it can be inferred that the choice of method depends on factors like the programming language [19] [20], the scale of the codebase, the types of clones to be detected, and the desired trade-off between accuracy and performance [21] [22]. However, the following are the main categories of algorithms that are most frequently used by researchers and industry.

1.2.1 Text-based Methods [23] [24]**:** These methods compare the textual similarity of code fragments by analyzing the source code as plain text. Techniques include string matching, token-based comparison, and n-gram analysis. Text- based methods for code clone detection analyze the code as plain text, focusing on the character-level or word-level similarities to identify potential code clones.

a. **String Matching** [25] [26]**:** This is the simplest approach where exact copies of code snippets are identified. Imagine two code blocks being compared, and if they are identical character-by-character (except for white spaces or comments), they are flagged as potential clones.

```
def calculate_area(length, width):
    area = length * width
    return area
```

```
def compute_area(length, width): # Identical code with a different function name
    area = length * width
    return area
```

Here, string matching would detect these code blocks as potential clones despite the difference in function names.

b. **Token-based Comparison** [27] [28]**:** This method breaks the code down into smaller units called tokens (like keywords, identifiers, operators, etc.) and compares the sequences of tokens. Even if variable names differ, the core functionality might be similar.

```
def calculate_area(length, width):
        area = length * width
        return area

def get_rectangle_area(l, w): # Different variable names but same logic
        area = l * w
        return area
```

Token-based comparison would recognize these code blocks as potential clones because the sequence of tokens (area, *, etc.) reflects the same operation despite variable name changes.

c. **N-gram Analysis** [29] [30]**:** This technique involves analysing overlapping sequences of characters (n-grams) within the code. By identifying frequent n-gram patterns across code segments, potential clones can be flagged. Here, 'n' refers to the number of characters in the sequence being compared. (bigrams for pairs, trigrams for triplets, and so on).

```
        def calculate_area(length,
  width): area = length * width
      return area

 def compute_area(ln, wd): # Different variable names, but similar
bigrams
      ar = ln *
  wd return ar
```

N-gram analysis (e.g., bigrams) might detect these code blocks as clones because they share common character sequences like "ea" and "ar*" despite the variations.

Text-based methods for code clone detection offer an easy, fast and straightforward approach, but they have limitations when dealing with clones that have undergone more significant structural or semantic changes.

However, they have their limitations as follows

d. Limitations of Text-based Methods [31] [32]**:**

- **Focus on Surface-Level Similarities** [33] [34]: Text-based methods primarily focus on the character-level or word-level similarities of the

code. They struggle to capture the underlying structure and logic behind the code, which can be crucial for identifying clones with significant changes.

- **Example:** Imagine two code blocks that achieve the same functionality but use entirely different control flow statements (e.g., loops vs. recursion). Text-based methods wouldn't recognize them as clones despite the same outcome because the character sequences would be very different.

b. **Sensitivity to Renaming and Reformatting** [35] [36]: These methods are sensitive to changes in variable names, formatting, and comments. Even if the core logic remains the same, these changes can disrupt the textual similarity and lead to missed clones.

- **Example:** Consider two code blocks with identical logic but different variable names and formatting. Text-based methods might not identify them as clones because they wouldn't match the exact character sequences.

c. **Inability to Handle Code Insertions/Deletions** [37] [38]: Text-based methods struggle with code segments that have significant insertions or deletions of code lines. These changes disrupt the overall textual pattern and make it difficult to identify the underlying similarities.

- **Example:** Token-based methods often fail when the code contains different identifiers or small structural variations, even if the underlying logic remains the same. Consider the following two functions, both of which compute the sum of a list:

```
+ ```python
+ def get_total(values):
+     total = 0
+     for v in values:
+         total += v
+     return total
```

```
+ ```
+
+ ```python
+ def sum_list(nums):
+     result = 0
+     for item in nums:
+         result = item + result
+     return result
+ ```
```

Token-based analysis treats these functions as different because the identifiers (values vs. nums, total vs. result), function names, and update expressions differ. However, n-gram-based analysis preserves recurring structural token patterns (initialization → loop → accumulation → return), allowing it to correctly identify these functions as clones despite the syntactic variations.

1.2.2 Lexical Analysis [39] [40]**:** These methods tokenize the source code and compare the token sequences to identify similar code fragments. This includes techniques like CCFinder, Deckard, and Nicad. The process includes:

a. **Tokenization** [41] [42]: The code is broken down into smaller units called tokens. These tokens can be keywords (like if, for), identifiers (variable names like x, y), operators (+, -), or other code elements.

b. **Sequence Comparison** [43] [44]: The sequence of tokens from different code fragments are compared. Tools such as CCFinder, Deckard, and Nicad use intricate algorithms to identify similarities in these sequences. For example,

```
#Python
def calculate_area(length, width):
    area = length *
width return area

def compute_area(length, width): # Identical code with a different function
name
    area = length *
width return area
```

Here, the lexical analysis identifies these code blocks as clones because the sequence of tokens (def, calculate_area,, length, etc.) would be the same.

In the case of Renamed Variables (Type-2 Clones)

```
Python
def calculate_area(length, width):
    area = length *
width return area

     def get_rectangle_area(l, w): # Different variable names but same
logic area = l * w
    return area
```

Lexical analysis would still recognize these as potential clones. Even though variable names (length vs. l) differ, the overall sequence of tokens (def, function_name, (, parameters, *, etc.) remains similar.

In case of Limited Code Changes (Near-Miss Clones), for example

```
Python
def calculate_area(length, width):
    area = length *
width return area

     def calculate_and_print_area(length, width): # Additional statement
added area = length * width
    print("Area of the square:",
area) return area
```

Lexical analysis can still be effective here [45] [46]. While an additional statement is present in the second code block, the core sequence of tokens (def, function_name, (, parameters, *, area, return) remains similar, indicating a potential clone with minor modifications. At the same time, it must be understood that Lexical analysis offers a good balance between efficiency and accuracy for clone detection. However, it can miss clones with significant structural changes (e.g., different control flow statements) or semantic variations (using completely different algorithms for the same purpose).

1.2.3 Syntax-based Methods [47] [48]: These analytical approaches and methods parse the source code and compare the abstract syntax trees (ASTs) or program dependency graphs (PDGs) to detect structural similarities [49] [50]. Basically, these Syntax- based methods delve deeper than just text or token sequences. They analyse the code structure to identify clones with similar functionalities even if the actual code looks different. Further this category of method can be categories into following techniques:

a. **Parsing:** The code is parsed to create an Abstract Syntax Tree (AST) which represents the code structure in a tree-like format. Each node in the tree represents a code element (e.g., function call, expression).

b. **AST Comparison:** Tools like CloneDR [51] [52], Simian [53], and Deckard [54] (which also utilizes lexical analysis) compare the ASTs of different code fragments. Nodes with similar structures and types are considered potential clones.

In case of Identical Code (Exact Clones)

```
def calculate_area(length, width):
    area = length *
width return area

def compute_area(length, width): # Identical code with a different function
name
    area = length *
width return area
```

Here, both code blocks would have identical ASTs. The comparison will reveal a perfect match, confirming them as exact clones.

In case of Renamed Variables with Same Logic (Type-2 Clones) [55] [56]**:**

```
def calculate_area(length, width):
    area = length *
width return area

     def get_rectangle_area(l, w): # Different variable names but same
logic area = l * width
    return area
```

Even though variable names differ, the overall structure of the ASTs would be identical. Both would have function definitions, variable assignments using multiplication, and a return statement. This indicates a strong possibility of a clone with renamed variables. This is biggest advantage of the AST based methods

Similar Logic with Different Control Flow (Type-3 Clones) [57] [58] **:**

```
def calculate_area_loop(side):
    area = 0
    for i in range(side):
         area +=
side return
area

def calculate_area_formula(side):
```

Here, the functionalities are similar (calculating area), but the control flow differs. One uses a loop for accumulation, while the other uses a formula. Syntax-based methods might still identify them as potential clones because the core structure of calculating area with side length as input remains similar in the ASTs [59] [60]. However, additional analysis might be needed to confirm this due to the control flow variation. Therefore, it should be noted that the Syntax-based methods offer a significant advantage over lexical analysis by considering the code structure. They can detect clones with variations in variable names or formatting but similar functionalities.

Syntax-based methods:

However, syntax-based methods only handle limited control-flow variation. They may still detect clones when the logic is equivalent but expressed through a different control construct (e.g., loop vs. formula). In contrast, they typically fail when the underlying

algorithm differs substantially (for example, two functions that both sort data but use different sorting algorithms). In such cases, the AST structures diverge too significantly for syntax-based comparison to match.

1.2.4 Semantic-based Methods [61] [62]: These methods analyze the program semantics, which includes, data and control flow to identify functionally similar code fragments. Hence, it can be safely said that these semantic-based methods go beyond the surface code structure and delve into the program's meaning and functionality. These methods aim to identify code fragments that perform similar computations or achieve the same results even if the code itself looks quite different syntactically. Techniques include PDG-based comparison and code property graph analysis. Here are the internal workings:

a. **Semantic Analysis** [63] [64]**: In this approach of analysis the** code is analyzed to understand its data flow (how data is manipulated) and control flow (how the program executes). Techniques like Program Dependence Graphs (PDGs) and code property graph analysis are used.

b. **Functional Comparison** [65] [66]: Tools employing semantic analysis compare the functionality and data manipulation logic across code fragments. They identify clones that achieve similar results despite syntactic variations. For example:

```
def calculate_area(length, width):
    area = length *
width return area

     def get_rectangle_area(l, w): # Different variable names but
same logic area = l * width
    return area
```

These code blocks, although potentially identified as clones by other methods too, would be confirmed as functionally equivalent by semantic analysis. Both calculate the area using multiplication, solidifying them as clones.

```
 Example: Different Control Flow with Same Functionality (Type-3 Clones)
: def calculate_area_loop(side):
    area = 0
    for i in range(side):
        area +=
 side return
 area
 def calculate_area_formula(side):
```

Here, the control flow differs (loop vs formula), but semantic analysis would

recognize that both functions aim to calculate the area using the side length and perform the same overall computation. This will flag them as potential clones despite the syntactic difference. When similar logic implemented

```
Differently (Type-4 Clones):
def sort_list_bubble(data):
   # Bubble sort
implementation swapped =
True
   while swapped:
      swapped = False
      for i in range(len(data) - 1):
         if data[i] > data[i + 1]:
            data[i], data[i + 1] = data[i + 1],
     data[i] swapped = True
   return data
def sort_list_builtin(data):
```

The above code listing demonstrates Type-4 clones, where the functionality (sorting a list) is the same but the implementation differs greatly. Semantic analysis would analyse the logic behind both functions (rearranging elements based on a comparison) and identify them as clones despite the use of a built-in function in the second case. Research shows that this approach is usually computationally expensive and might require domain-specific knowledge to fully understand the code's purpose.

1.2.5 Hybrid Methods: These combine multiple techniques, such as lexical and syntax-based analysis, to improve the accuracy and coverage of clone detection. Examples include CCAligner [67], SourcererCC [68], and NiCad [69].

1.2.6 **Machine Learning-based Methods:** These methods leverage deep learning models to learn code representations and detect clones, such as using graph neural networks on code property graphs. These are methods involves following steps:

i. **Code Representation:** The code is transformed into a format understandable by the machine learning model. This can involve techniques like tokenization, creating **Abstract Syntax Trees (ASTs)**, or using code property graphs (CPGs) [70].

ii. Code Property Graphs (CPGs): Here, the code structure is represented as a *graph* where nodes represent code elements (functions, variables) and edges represent relationships between them.

iii. Graph Neural Networks (GNNs) [80]: This type of deep learning model is adept at processing graph data. The CPG is fed into the GNN, which allows it to learn hidden patterns and relationships within the code structure.

iv. Clone Detection: Once trained on a dataset of labelled code clones (known similar and dissimilar code fragments), the GNN can analyse new code and predict the likelihood of it being a clone based on the learned patterns.

Machine learning models can learn complex patterns and adapt to new coding styles or languages, potentially overcoming limitations of traditional methods. These methods can handle large codebases efficiently also.

1.2.7 **Information Retrieval-based Methods:** These use information retrieval techniques like latent semantic indexing to identify similar code fragments based on textual and structural similarities. Information retrieval (IR) techniques can be used to identify similar code fragments based on both textual and structural information. Example scenario**:** Imagine you have a large codebase and want to find code clones. Traditional methods might struggle with complex variations, but IR techniques can help.

1.2.7.1 LSI for Code Clone Detection [81]:

i. **Code Representation:** LSI works with document collections. Here, each code snippet is treated as a document. Textual features like keywords, identifiers, and comments are extracted. Additionally, structural features such as function calls or variable declarations can be incorporated.

ii. **Term-Document Matrix:** A matrix is created where rows represent code snippets (documents) and columns represent features (keywords, structures). Each cell contains the weight reflecting the importance of that feature for a specific code snippet.

iii. **Dimensionality Reduction:** LSI reduces the dimensionality of the matrix by identifying latent semantic relationships between features. This helps capture the underlying semantic meaning beyond just individual words or structures.

iv. **Similarity Search:** New code snippets are compared to the transformed matrix. Based on the similarity score in the reduced space, potential code clones are identified. Consider two code fragments (A and B) with similar functionalities but some variations:

```
Code Fragment A:
def calculate_area(length, width):
    """ Calculates the area of a
rectangle""" area = length * width
    return area
Code Fragment B:
def get_rectangle_area(l, w):
    """ Calculates area based on length and
width""" result = l * w
    return result
```

Textual and Structural Features:

- Textual Features: "calculate", "area", "length", "width", etc. (both have similar keywords)
- Structural Features: Function definition, parameter passing, multiplication operation, etc. (both have similar structures)

LSI analyzes the features from both code snippets and identifies the underlying semantic relationship: "calculating area using length and width." The reduced space representation would capture this similarity despite some textual variations (e.g., "calculate" vs "get") and potentially identify them as clones based on their semantic closeness.

1.2.8 Visualisation-based Methods: These use code visualization techniques to help developers manually identify and analyze code clones. Visualization- based methods don't automate clone detection entirely, but instead, they use visual representations of code to assist developers in manually identifying and analysing code clones. Example case: you suspect code duplication in your project but traditional detection methods might overwhelm you with raw data and a lot of clutter or condensed information. Visualizations help to overcome such limitations or problems.

1.2.8.1 Code Clone Visualization Techniques involves [82]:

i. Comparing Side-by-Side View: This presents suspected code clones displayed side- by-side, highlighting the differences and similarities visually. Lines with identical code are colored the same, while variations are displayed differently.

ii. Clone Matrix Comparison [83]: In this the analyst creates a matrix where rows and columns represent code elements (functions, files). Cells within the matrix are shaded or coloured to indicate the degree of similarity between those elements. Darker shades or colours could represent higher similarity, making potential clone clusters visually identifiable.

iii. Code Heatmaps [84]: Here, code elements (lines, functions) are represented as a heatmap. The colour intensity in each cell reflects the level of complexity or potential duplication within that code section. Areas with similar color patterns could indicate potential code clones.

Visualising large codebases can become overwhelming and difficult to navigate. Techniques like clone matrices might be more suitable for high- level overviews. At the same time, subjectivity needs to be watched. The effectiveness of this approach depends on the developer's ability to interpret the visualizations and identify meaningful patterns.

```java
// ========== ORIGINAL ==========
public class Calculator {
    public int add(int a, int b) {
        // This method adds two numbers
        int result = a + b;
        return result;
    }

    public int multiply(int x, int y) {
        int product = x * y;
        return product;
    }
}
```

```java
// ========== CLONE ==========
public class MathOperations {
    public int addNumbers(int num1, int num2) {
        // This method adds two numbers
        int result = num1 + num2;
        return result;
    }

    public int multiplyNumbers(int a, int b) {
        int product = a * b;
        return product;
    }
}
```

Side by Side View

1.2.9 Metrics-based Methods [85]**:** These methods define metrics based on code characteristics like code size, complexity, and comments to identify code fragments with similar properties that might be potential clones. **Examples of Metrics-based Methods for Code Clone Detection**

Metrics-based methods are a preliminary approach to code clone detection. They analyse various code characteristics and identify code fragments with similar properties, potentially indicating clones. Here are some examples:

1.2.9.1 Lines of Code (LOC) Similarity [86]**:**

- This metric simply compares the number of lines in two code fragments. If the LOC is very similar, it suggests potential code duplication. For example,

```
    def calculate_area(length,
width): # Single line calculation
  return length * width

def get_rectangle_area(l, w):
  # Multi-line calculation with
comments area = l * w  # Calculate
area
  # Print the result (commented out)
#print("Area of the rectangle:",
area) return area
```

Here, both code fragments calculate the area, but the second one has additional comments. However, their LOC might be very similar, flagging them for further investigation as potential clones.

1.2.9.2 Cyclomatic Complexity Analysis [87]**:**

- This metric measures the potential decision-making paths within a code block. Higher complexity indicates more control flow structures (ifs, loops) and potentially more opportunities for code duplication. For example:

```
    def calculate_area_simple(length,
width): if length > 0 and width > 0:
        return length *
width else:
      return 0  # Handle invalid input

    def calculate_area_complex(length,
width): if length > 0:
      if width > 0:
            return length
 * width else:
         return 0 # Handle invalid
width else:
      return 0 # Handle invalid length
```

The first function has lower cyclomatic complexity (1) compared to the second one (2). However, both might have similar functionalities (area calculation with error handling), making them candidates for further analysis using other methods to confirm potential code clones.

1.2.9.3 Code Churn [88]**:**

This metric tracks the number of lines added, deleted, or modified within a code section over time. Similar churn patterns in different code fragments might indicate code duplication that has been modified independently. For example, think of two code blocks (A and B) that calculate square footage but were developed by different programmers. Over time, both functionalities underwent bug fixes and improvements, resulting in similar churn patterns (similar numbers of lines added/deleted) despite potential code variations. Metrics-based methods might flag them for investigation as

potential clones with independent modifications.

In fact, Metrics-based methods are a simple first step to identify potential code clones. Due to their limitations it can be inferred from the contemporary research works that they should be used in conjunction with other techniques like token-based comparison, syntax analysis, AST, or semantic analysis for more robust and accurate clone detection.

1.2.10 Tokenization with Edit Distance [89]**:** Similar to lexical analysis, these methods tokenize the code and then use edit distance algorithms like Levenshtein distance to measure the minimum number of edits required to transform one code fragment into another. This approach involves following sub methods:

i. **Tokenization:** Similar to lexical analysis, the code fragments are broken down into smaller units called tokens. These tokens can be keywords, identifiers (variable names), operators, or other code elements.

ii. **Sequence Comparison:** Edit distance algorithms like Levenshtein distance are used to measure the minimum number of edits (insertions, deletions, substitutions) required to transform the token sequence of one fragment into another.

iii. **Clone Detection:** Code fragments with a low edit distance are considered potential clones, as they share a very similar sequence of tokens despite potential variations.

For example, in the code listing below, it can be observed that both code fragments would be tokenized into similar sequences:

- Fragment A: def, calculate_area, (, length, width,), =, length, *, width, return, area
- Fragment B: def, get_rectangle_area, (, l, ,, w,), :, =, l, *, w, return, result

```
    def calculate_area(length, width): # Code
Fragment A area = length * width
   return area

    def get_rectangle_area(l, w): # Code
Fragment B result = l * w
   return result
```

Using Levenshtein distance, the minimum number of edits required to transform one sequence into another would be very low (likely 2 edits to replace "calculate_area" with "get_rectangle_area" and "length" with "l"). This suggests a high degree of similarity and flags them as potential clones. With understanding of the works related to this, it can be deduced that it should be combined with other methods like syntax using AST or semantic analysis for a more robust and accurate detection process. By using a combination of techniques, we can obtain a better understanding of code similarities and identify clones with various degrees of variation.

1.2.11 Fuzzy Matching Techniques [90]**:** These techniques go beyond exact string matching and allow for a certain degree of variation in token sequences to account for minor differences in variable names, formatting, or comments. The approach involves:

i. **Tokenization:** Similar to other methods, the code fragments are broken down into tokens (keywords, identifiers, operators, etc.).

ii. **Fuzzy Matching Algorithm:** Instead of exact string matching, algorithms like fuzzy string matching (e.g., Levenshtein distance with a threshold) or token-based similarity measures are used. These techniques allow for a certain degree of variation (e.g., maximum number of edits) when comparing token sequences.

iii. **Clone Detection:** Code fragments with a high similarity score based on the fuzzy matching algorithm are considered potential clones. This allows for some flexibility to account for minor differences

```
      def multiply_numbers(x, y): # Code Fragment
  A """This function multiplies two numbers"""
  product = x * y
        return product

  def calculate_product(a, b): # Code Fragment B (renamed
variables and comment)
        # Multiplies a and b and stores the result
  result = a * b
        return result
```

iv. Tokenization:

- Fragment A: def, multiply_numbers, (, x, ,, y,), :, """This function multiplies two numbers""",product,=,x,*,y,return,product`
- Fragment B: def, calculate_product, (, a, ,, b,), :, # Multiplies a and b and stores the result, result, =, a, *, b, return, result

v. Fuzzy Matching [91]**:**

Using a fuzzy matching algorithm with a threshold of 2 edits (allowing for

2 character changes), the token sequences would be considered highly similar. The algorithm would recognize the variations (renamed variables "x" to "a" and "y" to "b", and the added comment) and still find a strong match.

It should be noted that in this case, choosing the right threshold for allowed variations can be tricky. A high threshold might miss genuine clones, while a low threshold could introduce false positives. Furthermore, it should be understood that it is similar to edit distance, fuzzy matching still has limitations in understanding the deeper meaning or functionality of the code. This can lead to misidentifying clones with significant structural changes.

1.2.12 Context-Aware Matching: These methods consider the surrounding code context (e.g., function definitions, variable declarations) to improve the accuracy of clone detection and avoid identifying false positives due to isolated code similarities. Hence, it can be safely be said that in such an approach the researchers are going beyond just analysing individual code fragments. They consider the surrounding code context

to improve the accuracy of clone detection, especially when dealing with isolated code similarities that might not necessarily indicate clones.

Scenario: Imagine you suspect code duplication in your project, but some code snippets might share similar patterns due to common functionalities (e.g., mathematical operations) without being actual clones. Context-aware matching can help distinguish these cases.

The Approach:

i. **Code Analysis:** The code is analyzed beyond just tokens. Elements like function definitions, variable declarations, control flow structures, and call sites are considered.

ii. **Contextual Similarity:** Techniques like graph-based matching or context-aware tokenization are used. These methods compare not just individual tokens but also their relationships and positions within the surrounding code structure.

iii. **Clone Detection:** Code fragments with high contextual similarity are considered potential clones. This reduces false positives due to isolated code similarities.

```
    def calculate_area(length, width): # Code
Fragment A """Calculates the area of a rectangle"""
   area = length *
width return area

def calculate_distance(x1, y1, x2, y2): # Code Fragment B (uses similar
math operation)
   """Calculates the distance between two
points""" distance = ((x2 - x1) ** 2 + (y2 - y1) **
2) ** 0.5 return distance
```

Analysis without Context:

If we only analyse individual tokens, both fragments share similarities ("calculate", "*", etc.). This might lead to a false positive for a clone.

Context-Aware Analysis [91]**:**

By considering the context, the method would recognize that Fragment A is within a function calculating area (using length and width), while Fragment B is within a function calculating distance (using coordinates). This contextual difference would help distinguish them as not being clones despite the similar mathematical operation.

1.2.13. Clone Variation Analysis [92]**:** These techniques analyze the variations between code clones to understand the nature of changes made and potentially automate refactoring tasks.

The Approach involves:

i. **Clone Detection:** Techniques like those mentioned previously (token- based, syntax analysis, etc.) are used to identify code clones within the codebase.

ii. **Variation Analysis:** Once clones are identified, the specific variations between them are analyzed. This might involve:

- Identifying changed tokens and their positions.
- Analyzing control flow and data flow variations.
- Detecting variations in variable names, types, or function calls.

iii. **Refactoring Automation:** Based on the type of variations, tools might be able to automate some refactoring tasks. This could include:

- Renaming variables consistently across clones.
- Extracting common functionality into reusable functions.
- Applying code formatting changes to achieve consistency.

Code Fragment A (Variation):

```
    def calculate_area(length, width): """Calculates the area of a
rectangle""" if length > 0 and width > 0:
        area = length * width else:
        area = 0 return area

def get_rectangle_area(l, w): # Renamed function and variables
  """This function calculates the area of a rectangle (with error
handling)""" if l <= 0 or w <= 0:
      raise ValueError("Invalid input: Length and width must be positive")
```

Code Fragment B (Variation):

```
    result = l * w return result
```

Variation Analysis:

- Function name change ("calculate_area" to "get_rectangle_area")
- Variable name change ("length" and "width" to "l" and "w")
- Added comments in Fragment B
- Different error handling approach (if statement vs. raising an exception)

Refactoring Automation:

- Tools might be able to automatically rename variables ("l" and "w") to be consistent with Fragment A.
- Extracting the common logic for area calculation into a separate function could be recommended.

Clearly. With the help of this approach and by analysing the variations between code clones, developers can make better decisions about refactoring and potentially automate repetitive tasks, leading to a more maintainable and cleaner codebase

1.2.14. Clone Lineage Tracking: These methods track the evolution of code clones over time to identify how they have been modified and potentially predict future

changes or code smells. Clone lineage tracking goes beyond simply detecting code clones at a specific point in time. In this class of methods, the developer conducts a deeper analysis of tracking how these clones have evolved and changed throughout the project's history, providing valuable insights into code maintainability and potential issues. For example, think of a scenario in which you're working on a large codebase with a history of modifications. Clone lineage tracking can help you understand how code clones have been modified and identify potential areas for improvement.

The approach involves:

i. **Version Control System (VCS) Analysis** [93]**:** The code version control system (e.g., Git) is used to track changes made to the codebase over time.

ii. **Clone Detection in Different Versions** [94]**:** Code clone detection techniques (like those mentioned previously) are applied to different versions of the codebase to identify clones across history.

iii. **Lineage Analysis:** The relationships between clones in different versions are analysed to understand how they have been modified and evolved. This involves:

- Identifying code fragments added, removed, or modified within clones.
- Tracing the history of changes within each clone lineage.

Clone lineage tracking is useful for analysing the evolution of code clones within a project. By understanding how clones have changed over time, developers can identify areas for improvement, predict potential code smells, and make informed decisions about code maintenance and refactoring. This technique can be particularly useful for large codebases with a long history of modifications

1.2.15. Clone Cluster Analysis or Unsupervised Machine Learning [95] [96]**:** These techniques group similar code clones together to identify common patterns and potentially refactor entire code blocks for better maintainability. So basically, clone cluster analysis leverages unsupervised machine learning techniques to group similar code clones together. This allows developers to identify common patterns within these

clusters and potentially refactor entire code blocks for improved maintainability. This method is referred to as an unsupervised method in the class of machine learning algorithms. Technically, by doing clone cluster analysis, the characteristics of each cluster convey a pattern that may be a pattern of similarities or dissimilarities.

1.2.16 Feature Analysis and Extraction:

It is important to understand that in the domain of machine learning, whether it is supervised or unsupervised, there is always a need to extract 'features' or attributes that will inherently have inherent distinctive and predictive properties. The slight difference between original code and cloned code need to be computed mathematically and it has to be significant for such methods to work properly. The design and selection from the data is critical.

Code clone detection systems typically utilize multiple categories of features to capture different aspects of code similarity. Lexical features analyze the code as text, examining token frequencies, keyword distributions, and information-theoretic measures like entropy, which help identify patterns in the raw character and token sequences. Structural features, derived from the Abstract Syntax Tree (AST), capture the organizational framework of the code, including node counts, tree depth, branching factors, and the distribution of syntactic elements, providing insight into the code's architectural blueprint. Semantic features delve into the program's meaning by analyzing control and data flow dependencies, cyclomatic complexity, and method invocation patterns, revealing how the code behaves during execution. Each category contributes a unique perspective; lexical features are efficient but shallow, structural features offer deeper syntactic insight, and semantic features provide the richest understanding of code functionality. Combining these complementary feature types creates a robust representation that can detect clones across a spectrum of code modifications.

Once code is transformed into feature vectors, the detection of clones becomes a mathematical problem of measuring similarity or distance between these vectors in a multi-dimensional space. Various distance metrics are employed to quantify these differences, each suitable for different types of feature representations. Euclidean

distance calculates the straight-line distance between vectors, providing a geometric measure of overall dissimilarity. Cosine similarity measures the angular separation between vectors, making it particularly effective for high-dimensional sparse data by focusing on orientation rather than magnitude. Jaccard similarity compares sets of elements, ideal for token-based features where presence or absence matters more than frequency. These mathematical transformations allow the subtle differences between original and cloned code to be computed numerically, creating a continuum of similarity scores that can be thresholded or clustered to identify clone pairs. The choice of distance metric significantly influences detection performance, as it determines how feature differences are weighted and interpreted

Given the high dimensionality of potential features, feature selection strategies are crucial to identify the most informative attributes while eliminating redundant or noisy ones. Filter methods employ statistical tests to evaluate features independently of any specific machine learning algorithm, using measures like information gain, chi-square tests, or correlation coefficients to rank features by their discriminative power. These methods are computationally efficient and provide a general assessment of feature relevance. Wrapper methods, in contrast, evaluate feature subsets by their actual performance on a specific machine learning model, using techniques like forward selection or recursive elimination to iteratively build optimal feature sets. While more computationally intensive, wrapper methods often yield features better tailored to the particular algorithm's characteristics. Both approaches aim to create a parsimonious feature set that maximizes the mathematical significance of differences between clones and non-clones while minimizing dimensionality and overfitting risks

Chapter-2

REVIEW OF LITERATURE

Even with the availability of AI-assisted tools like Chatgpt and GitHub [99], research into code cloning remains relevant. While these tools can aid in software development and reduce development time, code cloning remains a significant threat to software security and dependability. In this Chapter, we will therefore learn more about the research conducted in this context.

Code cloning, according to the authors [100], occurs when identical or similar code fragments are reused in different parts of a software system. This can result in a number of issues, including increased maintenance costs, diminished code quality, and heightened susceptibility to security threats. For instance, if a security flaw exists in a code fragment that has been cloned, it can spread to multiple parts of the system, making it more difficult to identify and resolve the issue [101].

AI-assisted tools like Chatgpt, Deepseek, Claudi and GitHub Copilot can aid in the identification and analysis of code clones, but they are not a comprehensive solution. Code cloning is a complex problem that necessitates a multifaceted approach, including software engineering practices, tool support, and developer awareness and education [102]. Optimization approaches, machine learning algorithms [101], deep learning models [103] [104], and meta-learning are useful in a variety of ways for detecting code cloning [105], as evidenced by the current state of research in this area.

By comparing the similarity of code fragments, source comments [106], optimization techniques can be used to detect duplicate code. In the research [107], the Levenshtein distance algorithm can be used to determine the degree of similarity between two text strings, which can then be used to identify code clones.

Large datasets of code are used to train machine learning algorithms to identify patterns of code duplication. Researchers have, for instance, used machine learning techniques such as clustering and classification to identify code clones in large codebases [108]. By analysing the syntax and structure of code fragments, techniques of deep learning such as convolutional neural networks (CNNs) can be used to detect code clones.

Researchers have used CNNs to detect code clones in C [108]] and Java [109] code, for instance.

Today, meta-learning pipelines, ensembles and techniques are commonly used to discover the most effective strategies for detecting code clones across various codebases and programming languages [110] [111]. In addition, the current literature indicates that these techniques can be combined (hybridization) to create more accurate and effective tools for detecting code clones. For instance, researchers have proposed the DeepCC framework [112], which combines deep learning and optimization techniques [113] to detect code clones with high precision and efficiency. Other researchers [114] have proposed using meta-learning to develop code clone detection algorithms that are more effective and can adapt to various programming languages and codebases. These advancements in optimization, machine learning, deep learning and meta-learning are enhancing the precision and efficiency of code clone detection, which is essential for enhancing software security and reliability. Scalability is a significant challenge for code clone detection tools [115].

Numerous existing techniques are computationally costly, limiting their applicability to large codebases. As the size and complexity of codebases continue to increase, there is a need for more scalable and effective code clone detection techniques [116]. Code clone detection techniques can be susceptible to false positives and false negatives [117], leading to inaccurate or insufficient results. False positives can lead to extra work for developers, while false negatives can result in missed opportunities for optimization and improvement. Techniques for detecting code clones must be compatible with multiple programming languages. Different languages have different syntax and structure, making it difficult to develop a one-size-fits-all solution to this problem.

Many code clone detection techniques are based on static analysis, meaning they may not be able to detect code clones in dynamically generated or runtime-modified code. Code clone detection techniques may raise privacy concerns because they require

access to vast quantities of code to train machine learning models or conduct analysis. This can be a concern for code that is proprietary or confidential.

Token-based code clone detection has emerged as a significant technique in software engineering, with researchers exploring its applications across various programming languages. The authors [116] implemented this method for Dart, demonstrating its effectiveness by successfully detecting all injected clones in their evaluation. They posited that the approach could be extended to other languages like Java and C++, highlighting its versatility. This adaptability across languages suggests broad applicability in diverse software development environments. [117] proposed a customizable tokenization mechanism to enhance the efficiency of clone detection. They noted that while token-based approaches yield good results with minimal code transformation, they can be computationally expensive due to the large search space. This observation points to a crucial trade-off between detection accuracy and processing efficiency that researchers must navigate. Their work on flexible tokenization aimed to address this challenge, potentially opening avenues for optimizing the technique for specific use cases or programming paradigms. Earlier research by [118] had already demonstrated the effectiveness of token-based techniques in identifying various types of code clones, including exact, renamed, and gapped clones. This versatility in detecting different clone types underscores the method's value in comprehensive code analysis and maintenance tasks. The ongoing research in this field, spanning from 2004 to 2022 and beyond, indicates that token- based code clone detection remains an active area of study with continuous refinements and improvements. Researchers [119] have employed various evaluation methods, such as injecting known clones, to validate their techniques, providing insights into the robustness of these approaches. Moreover, the potential for customization, as explored by [120], suggests that token-based methods can be tailored to meet specific project requirements or language peculiarities, further enhancing their utility in diverse software development contexts. As software systems grow in complexity and scale, efficient and accurate code clone detection becomes increasingly crucial for maintaining code quality, reducing redundancy, and facilitating software evolution. The continued exploration and enhancement of token-based techniques contribute significantly to addressing these challenges in modern software engineering practices.

The research by [121] represents a good level of advancement in the field of code clone

detection, introducing a novel approach that leverages graph theory and machine learning techniques. Their proposed tool, CCGraph, utilizes Program Dependence Graphs (PDGs) and graph kernels to identify code clones with improved accuracy and efficiency.

The use of PDGs in CCGraph is particularly noteworthy as it allows for a more semantic representation of code structure compared to traditional token-based or syntax-based approaches. By normalizing the structure of PDGs, [121]. Aimed to reduce the impact of superficial code differences while preserving the underlying logical flow and data dependencies.

A key innovation in CCGraph is the two-stage filtering strategy employed to reduce the number of candidate clone pairs. This approach likely contributes significantly to the tool's improved efficiency, addressing one of the major challenges in PDG-based clone detection: the computational complexity of graph comparisons [121].

The incorporation of the Weisfeiler-Lehman (WL) graph kernel for approximate graph matching is yet another important aspect of CCGraph. Graph kernels are powerful tools in machine learning for comparing graph structures, and the WL kernel, in particular, is known for its ability to capture both local and global graph properties. This choice suggests that CCGraph can detect clones that share similar structural and semantic properties, even if they're not identical in syntax.

The experimental results reported by [121] are particularly encouraging. The improved recall and F1-score compared to other state-of-the-art PDG-based tools indicate that CCGraph is more effective at identifying a wider range of code clones, including those that might be missed by other detectors. The mention of better detection of semantic clones is especially significant, as semantic clones (code fragments that perform the same function but may look different) are often the most challenging to identify automatically [121].

The reported efficiency gains of CCGraph over existing PDG-based clone detectors are also noteworthy. This improvement addresses one of the primary drawbacks of PDG-based approaches – their typically high computational cost. By achieving better

performance without sacrificing detection quality, CCGraph potentially makes PDG-based clone detection more practical for large-scale software projects.

It's worth considering the potential implications of this research for the broader field of software engineering. Improved code clone detection can lead to better code maintenance, refactoring, and overall software quality. Tools such as CCGraph can be integrated into development environments to provide real-time feedback to developers, helping to prevent the introduction of unnecessary code duplication.

However, it's important to note that while CCGraph shows promising results, further research may be needed to validate its performance across a wider range of programming languages and project types. Additionally, the complexity of setting up and using PDG-based tools compared to simpler token-based approaches might still be a barrier to widespread adoption in some development contexts.

Clearly, the work by Zou et al. on CCGraph [121] represents a significant step forward in code clone detection technology, combining advanced graph theory concepts with practical software engineering needs. It demonstrates the ongoing potential for innovation in this field and the value of interdisciplinary approaches in solving complex software engineering challenges.

The research in code clone detection has seen significant advancements over the years, with various approaches tackling the challenge from different angles. The work of [124] on SourcererCC represents a notable advancement in token-based clone detection techniques. By leveraging locality sensitive hashing, they achieved a scalable solution that addresses one of the primary challenges in clone detection: efficiently processing large codebases. The superior performance of SourcererCC in terms of both precision and recall underscores the potential of innovative algorithmic approaches in this field.

However, the limitation of SourcererCC to exact and near-miss clones highlights an ongoing challenge in code clone detection. While these types of clones are important to identify, they represent only a subset of the code duplication issues that can impact software quality and maintainability. The inability to detect more complex semantic clones points to the need for complementary approaches or further refinements in

token-based techniques.

However, the noted limitation of token-based approaches in detecting clones with significant structural differences but similar functionality points to a fundamental challenge in this approach. This limitation stems from the fact that token-based methods primarily focus on textual similarity, which may not always correspond to functional similarity.

The emergence of graph-based approaches, exemplified by CCGraph, represents a significant shift in clone detection strategies. By leveraging program dependency graphs, these techniques can capture semantic relationships within code that may not be apparent from token sequences alone. This capability allows for the detection of semantic clones, which are often the most challenging to identify but can be among the most important for code maintenance and refactoring.

The ability of graph-based approaches to detect semantic clones is particularly valuable in modern software development practices. As codebases grow larger and more complex, identifying functionally similar code segments becomes crucial for maintaining code quality, reducing redundancy, and facilitating code reuse. However, the potential scalability issues with graph-based approaches highlight the trade-offs inherent in different clone detection strategies.

The recognition that hybrid approaches [125] combining multiple techniques may be a promising direction for improving overall performance in code clone detection is a key insight. Such approaches could potentially leverage the strengths of different methods while mitigating their individual weaknesses. For instance, a hybrid system might use token-based methods for initial, rapid screening of large codebases, followed by more intensive graph-based analysis on subsets of code identified as potential clones [126].

It's worth considering the broader implications of these advancements in code clone detection [127]. Improved clone detection capabilities can significantly impact software development practices, potentially leading to enhanced code quality and maintainability through easier identification of redundant code. It will help to be more efficient refactoring processes, as developers can more readily identify opportunities for code

consolidation. Besides, it will help to improve software security, as cloned code often propagates vulnerabilities across a system. Consequently, it leads to Better understanding of code evolution and software architecture through analysis of clone patterns. However, the development of more advance clone detection techniques also raises new challenges. As these tools become more powerful, there's a need for better integration into development workflows and IDEs to make them accessible and useful to developers in real-time [128]. Additionally, there's a growing need for tools that not only detect clones but also assist in determining which clones should be refactored and how.

The ongoing research works [129] in this field also points to the potential for applying machine learning and AI techniques to further enhance clone detection capabilities. These could potentially help in identifying subtler patterns of code duplication and even predict areas where clones are likely to occur in future development. The evolution of code clone detection techniques from simple token-based approaches to sophisticated graph-based and hybrid methods reflects the growing complexity of software systems and the increasing importance of effective code management.

Code clone detection has become an increasingly important area of research in software engineering, with various approaches being developed to identify and manage duplicated code. Among these approaches, lexical analysis has emerged as a fundamental component of many codes clone detection systems, offering a balance between simplicity and effectiveness.

The work of [130] on CCFinder exemplifies the power of token-based code clone detection utilising lexical analysis. By extracting token sequences from source code and applying normalisation rules, CCFinder demonstrates the ability to detect a range of clone types, including exact, renamed, and gapped clones. This versatility highlights the adaptability of lexical analysis in capturing various forms of code duplication. The robustness of this approach against minor code changes such as formatting, spacing, and variable renaming is particularly noteworthy, as it allows for the identification of clones that might be missed by more rigid detection methods.

However, the limitations of token-based approaches, as observed in CCFinder,

underscore the complexity of comprehensive code clone detection. The potential to miss clones with significant structural differences, but similar functionality points to the need for complementary techniques that can capture semantic similarities beyond lexical patterns.

The comparative study by [131] provides valuable insights into the strengths and weaknesses of lexical analysis versus syntactic analysis in code clone detection. Their characterization of the lexical approach as providing a "crude overview" of duplicated code aligns with the broader understanding that token-based methods offer a quick and efficient way to identify potential clones across large codebases. This efficiency makes lexical analysis particularly suitable for initial problem detection and assessment, especially in scenarios where rapid analysis of extensive code repositories is required.

On the other hand, the observation that syntactic analysis, based on Abstract Syntax Trees (ASTs) [132], can reveal duplicated subroutines more precisely highlights the complementary nature of different clone detection approaches. The ability of AST-based methods to capture structural similarities that might be missed by lexical analysis suggests a more nuanced understanding of code duplication, particularly useful for fine-grained refactoring efforts.

The distinction drawn by [131]. between the applications of lexical and syntactic approaches provides valuable guidance for practitioners and researchers in the field of code clone detection. It suggests a multi-stage approach to clone detection might be optimal, where lexical analysis is used for broad, initial scans, followed by more detailed syntactic analysis for areas of interest identified in the first stage.

This layered approach to code clone detection aligns with the evolving needs of software development practices, where both efficiency and precision are crucial. As codebases grow larger and more complex, the ability to quickly identify potential areas of duplication (through lexical analysis) and then perform more detailed examinations (through syntactic or semantic analysis) becomes increasingly valuable.

Furthermore, the insights from these multiple studies point to the potential for hybrid approaches that combine the strengths of multiple detection techniques. Such hybrid

systems could leverage the speed and breadth of lexical analysis for initial screening, followed by the precision of syntactic or semantic analyses for confirmed areas of interest. This multi-faceted approach could provide a more comprehensive and nuanced view of code duplication within software projects.

The ongoing research works [133] [134] in this field also suggests potential areas for future development. For instance, the integration of machine learning techniques could enhance the ability of lexical analysis to identify more complex patterns of duplication, potentially bridging the gap between lexical and syntactic approaches [135]. Additionally, the development of more sophisticated normalisation rules could further improve the robustness of token-based methods against superficial code variations [136].

The work of [137] provides a comprehensive comparative analysis of various code clone detection techniques, offering valuable insights into the strengths and limitations of different approaches, including those based on lexical analysis. Their research highlights the complex trade-offs involved in selecting and implementing code clone detection methods, particularly in the context of large-scale software systems.

The finding that lexical analysis-based methods are computationally expensive due to the large search space is a crucial observation. This computational cost stems from the need to compare vast numbers of token sequences across an entire codebase, which can become increasingly challenging as the size and complexity of software projects grow. However, this limitation must be balanced against the effectiveness of lexical analysis in detecting various types of clones, including exact, near-miss, and some forms of semantic clones.

The ability of lexical analysis to identify different clone types underscores its versatility as a detection technique. This capability is particularly valuable in real- world software development scenarios, where code duplication can manifest in various forms due to factors such as copy-paste programming, parallel development, or the evolution of code over time. The effectiveness of lexical analysis in capturing this diversity of clone types contributes to its continued relevance in code clone detection research and practice.

The authors [137] suggestion of a hybrid approach combining multiple techniques represents a forward-thinking perspective on addressing the challenges of code clone detection. This recommendation acknowledges that no single technique is likely to be optimal for all scenarios and types of clones. A hybrid approach could potentially leverage the strengths of different methods while mitigating their individual weaknesses.

For instance, a hybrid system might use lexical analysis for an initial, broad-scale scan of the codebase to identify potential clone candidates quickly. This could be followed by more computationally intensive techniques, such as semantic analysis or abstract syntax tree comparisons, applied selectively to the identified candidates. Such an approach could balance the need for comprehensive clone detection with practical considerations of computational efficiency.

Furthermore, the concept of a hybrid approach opens up possibilities for integrating emerging technologies and methodologies into code clone detection systems. Machine learning and artificial intelligence techniques, for example, could be incorporated to enhance the accuracy and efficiency of clone detection, potentially learning from patterns identified through lexical analysis to improve overall system performance.

The researchers' findings also highlight the need for ongoing research and development in optimizing lexical analysis-based methods. Techniques such as improved tokenization algorithms, more sophisticated filtering mechanisms, or parallel processing approaches could help address the computational challenges associated with large search spaces. Moreover, the development of more nuanced similarity metrics could enhance the ability of lexical analysis to distinguish between meaningful code clones and incidental similarities.

It's worth considering the broader implications of these findings for software engineering practices. As software systems continue to grow in size and complexity, the importance of efficient and effective code clone detection becomes increasingly critical. Clones can impact software quality, maintainability, and even security, making their detection and management an essential aspect of the software development lifecycle.

The insights provided by [137] work also shows the importance of context-specific selection of clone detection techniques. Depending on the specific needs of a project – such as the size of the codebase, the programming languages used, or the types of clones of particular concern – different approaches or combinations of approaches may be most appropriate. This highlights the need for flexible, configurable clone detection tools that can be tailored to the specific requirements of different software projects.

Clearly, these works indicate that lexical analysis-based techniques, such as CCFinder, can effectively detect various types of code clones, including exact, renamed, and gapped clones. However, these techniques may miss more complex, semantically similar clones and can be computationally expensive for large codebases. Combining lexical analysis with other techniques, like syntax-based or graph-based analysis, is a promising direction to address the limitations of the lexical approach. And at the same time, it can be inferred that hybrid approaches are also good in finding clones.

The seminal work of [131] on "Clone Detection Using Abstract Syntax Trees" represents a significant milestone in the evolution of code clone detection techniques. Their comparative analysis of lexical (token-based) and syntactic (AST-based) approaches provides crucial insights into the strengths and limitations of different clone detection methodologies, shaping the direction of subsequent research in this field.

The researchers' finding that the AST-based approach can reveal duplicated subroutines more precisely than the lexical approach highlights a fundamental difference in the level of code comprehension between these two methods. Abstract Syntax Trees capture the structural and hierarchical nature of code, preserving relationships between different code elements that may be lost in a simpler token- based representation. This structural awareness allows AST-based methods to identify more complex patterns of code duplication, particularly those involving similar logical structures with potentially different surface-level syntax.

The superiority of the AST-based approach in fine-grained refactoring scenarios stems from its ability to provide a more nuanced understanding of code structure [137]. By representing code as a tree of syntactic elements, AST-based methods can more easily identify opportunities for restructuring and optimization that might not be apparent

from a purely lexical analysis. This capability is particularly valuable in modern software development practices, where code refactoring is an ongoing process aimed at improving maintainability, readability, and efficiency.

However, the researchers' observation that the lexical approach is more suitable for initial problem detection and assessment underscores the continuing relevance of token-based methods in code clone detection. The simplicity and efficiency of lexical analysis make it well-suited for rapid, large-scale scans of codebases, providing a quick overview of potential duplication issues. This "first pass" capability is crucial in real-world software development environments, where time and computational resources may be limited.

The dichotomy between AST-based and lexical approaches highlighted by Baxter et al. points to a broader principle in code clone detection: the trade-off between precision and scalability. AST-based methods offer greater precision but may be more computationally intensive, especially for large codebases. Lexical methods, while potentially less precise, can quickly process vast amounts of code to identify areas of interest for further investigation.

This insight has significant implications for the design of comprehensive code clone detection systems. It suggests that an effective approach might involve a multi-stage process, beginning with a broad lexical analysis to identify potential clone candidates, followed by a more detailed AST-based analysis of these candidates. This layered approach could balance the need for both breadth and depth in clone detection, leveraging the strengths of each method.

Furthermore, the work of Baxter et al. has influenced the development of hybrid and enhanced clone detection techniques. Researchers have explored ways to combine the efficiency of lexical analysis with the precision of AST-based methods, leading to more sophisticated algorithms that can adapt to different types of code clones and varying project requirements.

The distinction between initial problem detection and fine-grained refactoring highlighted in this research also aligns with different stages of the software

development lifecycle. During early development or when analysing legacy code, a quick lexical scan can provide valuable insights into the overall state of code duplication. As development progresses or during targeted refactoring efforts, the more precise AST-based approach becomes invaluable for making informed decisions about code restructuring.

It's worth noting that since the publication of Baxter et al.'s work, advancements in computing power and algorithm efficiency have somewhat mitigated the performance gap between lexical and AST-based approaches. However, the fundamental trade- offs and strengths of each method remain relevant, particularly when dealing with extremely large codebases or in resource-constrained environments. The insights provided by this research have also influenced the development of integrated development environments (IDEs) and code analysis tools. Many modern tools incorporate both lexical and syntactic analysis capabilities, allowing developers to switch between high-level overviews and detailed structural analyses as needed.

The research by [138] on "Method-level Code Clone Detection on Transformed Abstract Syntax Trees" represents a significant advancement in the field of code clone detection, particularly in addressing the limitations of both token-based and traditional AST-based approaches. This work builds upon the foundation laid by earlier researchers like Baxter et al. (1998) while introducing innovative techniques to enhance the effectiveness of clone detection at the method level.

Greenan's [138] approach of transforming Abstract Syntax Trees (ASTs) before applying sequence matching algorithms is a novel contribution that addresses some of the inherent challenges in AST-based clone detection. By modifying the structure of the ASTs, this method creates a representation that is more conducive to sequence matching, potentially increasing both the efficiency and accuracy of the clone detection process.

The focus on method-level clone detection is particularly noteworthy. Methods (or functions) are fundamental units of code organization and reuse in most programming paradigms. By targeting clone detection at this level, Greenan's [138] approach aligns well with how developers typically think about and structure their code. This method-

centric view can provide more actionable insights for refactoring and code improvement compared to approaches that focus on smaller code fragments or larger structural units.

The effectiveness of this transformed AST approach in detecting clones missed by token-based techniques, especially for code with significant structural differences, highlights a key advantage of syntax-aware methods. Token-based approaches, while efficient for detecting surface-level similarities, can struggle with code that has been substantially reorganised or refactored while maintaining similar functionality. By leveraging the structural information captured in ASTs, Greenan's method [138] can identify these more subtle forms of code duplication.

This capability is particularly valuable in modern software development practices, where code evolution and refactoring are constant processes. As codebases grow and evolve, the ability to detect functionally similar code segments that have diverged in their syntactic structure becomes increasingly important for maintaining code quality and preventing unintended duplication. Moreover, the use of sequence matching algorithms on the transformed ASTs represents an interesting hybrid approach, combining elements of both structural and textual similarity detection. This combination potentially offers a balance between the precision of AST-based methods and the efficiency of sequence matching techniques commonly used in text-based clone detection. However, it's important to consider potential limitations of this approach. The transformation of ASTs and subsequent sequence matching may introduce additional computational complexity compared to simpler token-based methods. This could impact the scalability of the approach for very large codebases or in scenarios where real-time analysis is required.

Furthermore, the effectiveness of the AST transformation process may vary depending on the specific programming language and coding styles used. Different languages with varying syntactic structures might require tailored transformation strategies to achieve optimal results. The work also raises interesting questions about the nature of code similarity and what constitutes a "true" clone. As detection methods become more sophisticated in identifying structurally different but functionally similar code

segments, the definition of what should be considered a clone may need to evolve.

The research by [139] on "Source Code Plagiarism Detection Based on Abstract Syntax Trees" represents a significant advancement in the application of AST-based techniques to the critical problem of code plagiarism detection. Their system, CodEX, showcases the power and versatility of Abstract Syntax Tree representations in capturing the essence of code structure and functionality, even in the face of deliberate attempts to obfuscate similarities.

The combination of AST-based fingerprinting, node hashing, and similarity calculations in CodEX demonstrates a multi-faceted approach to code analysis. This layered strategy allows for a nuanced understanding of code similarity that goes beyond surface-level comparisons. By leveraging the structural information encoded in ASTs, CodEX can identify similarities in code logic and organisation that might be missed by simpler token-based or lexical analysis methods.

The impressive 95% success rate in identifying test cases highlights the effectiveness of this approach. This high accuracy is particularly noteworthy given the challenging nature of plagiarism detection in academic settings, where students may employ various techniques to disguise copied code. The ability of CodEX to overcome these obfuscation attempts speaks to the robustness of AST-based methods in capturing the fundamental structure of code, regardless of superficial changes. This research has significant implications beyond just plagiarism detection. The techniques employed in CodEX could be adapted for broader code clone detection purposes in software development, potentially improving code quality and maintenance practices. By identifying structural similarities across a codebase, developers could more easily refactor redundant code, improve modularity, and ensure consistency in coding patterns.

The success of CodEX [139] also underscores the growing importance of sophisticated code analysis tools in both academic and professional settings. As programming education becomes more widespread and software systems grow in complexity, the need for reliable, automated methods to assess code originality and identify potential instances of plagiarism or unauthorized code reuse becomes increasingly critical.

However, the use of AST-based methods like those employed in CodEX is not without challenges. The process of constructing and comparing Abstract Syntax Trees can be computationally intensive, especially for large codebases or when dealing with a high volume of submissions in an academic context. This computational complexity can potentially limit the scalability of such systems, particularly in scenarios requiring real-time or near-real-time analysis. It can be observed, while AST-based approaches excel at capturing structural similarities, they may sometimes struggle with cases of functional similarity where the code structure differs significantly. This limitation suggests that the most comprehensive code analysis systems might need to combine AST-based methods with other techniques, such as semantic analysis or machine learning approaches, to cover a wider range of similarity types. The research by many other researchers also raises interesting questions about the nature of code similarity and originality in programming. As detection methods become more sophisticated, there may be a need to refine our understanding of what constitutes acceptable code reuse versus plagiarism, particularly in educational settings where students are often learning from examples and adapting common solutions to problems. Clearly, the work of Zheng et al. on CodEX demonstrates the significant potential of AST-based approaches in code analysis and plagiarism detection. While challenges remain, particularly in terms of computational complexity and scalability, the high accuracy and robustness of this method suggest that AST-based techniques will play an increasingly important role in code analysis, quality assurance, and academic integrity efforts. As software continues to permeate every aspect of our lives, the ability to effectively analyse and understand code similarities and differences will become ever more crucial, making research in this area vital for the future of software engineering and computer science education.

The field of semantic-based code clone detection has seen significant advancements in recent years, with researchers exploring various innovative approaches to capture the functional similarities between code fragments that go beyond syntactic or structural resemblances. These semantic approaches represent a crucial evolution in clone detection techniques, addressing the limitations of earlier methods that relied primarily on textual or structural similarities.

[140] work on SrcSlice exemplifies the potential of code slicing in semantic clone detection. Their two-stage clustering approach leverages the power of code slicing to isolate functionally relevant parts of the code. This method allows for a more focused analysis of code behaviour, potentially identifying semantic similarities that might be obscured by differences in code structure or syntax. The use of clustering in their approach suggests an attempt to group functionally similar code fragments efficiently, which could be particularly valuable when dealing with large codebases.

[141] feature vector-based approach represents another innovative direction in semantic clone detection. By using data types, control blocks, and method calls as features, their method captures key aspects of code functionality. This approach can potentially identify semantic similarities even when the superficial structure of the code differs significantly. The use of feature vectors also opens up possibilities for applying machine learning techniques to further enhance clone detection accuracy and efficiency.

The work of [142] introduces the concept of comparing abstract memory states to detect semantic clones. This approach dives deep into the behavioural aspects of code, analysing how different code fragments manipulate memory. By focusing on these abstract states, MeCC can potentially identify functionally equivalent code that might look very different on the surface. This method could be particularly useful in identifying complex semantic clones that other approaches might miss.

[143] algorithm, which reduces graph similarity to tree similarity for detecting semantic clones, represents an interesting bridge between structural and semantic approaches. By transforming the complex problem of graph similarity into a more manageable tree similarity problem, this method potentially offers a balance between the depth of semantic analysis and computational efficiency. This approach could be particularly useful in scenarios where maintaining some level of structural analysis is beneficial while still capturing semantic relationships.

[144] The EqMiner tool proposed by Farmahini et al., which focuses on input-output behaviour, brings yet another perspective to semantic clone detection. By examining how code responds to various inputs, this approach can identify functionally equivalent

code segments regardless of their internal structure. This method aligns well with the concept of behavioral equivalence in software engineering.

The diversity of these approaches highlights the complexity of semantic clone detection and the multifaceted nature of code similarity. Each method offers unique strengths and weaknesses. Code slicing focuses on isolating functionally relevant code segments. Feature vector approaches capture key characteristics that define code behavior and Abstract memory state comparison delves into the detailed effects of code execution. The concept of Input-output behavior analysis aligns with black-box testing principles is useful but at the same time it can be observed from the current survey that Graph-to-tree similarity reduction offers a compromise between structural and semantic analysis. This variety of techniques also suggests that a comprehensive semantic clone detection system might benefit from combining multiple approaches. such a hybrid system could leverage the strengths of each method to provide a more robust and accurate clone detection capability.

The application of machine learning techniques, particularly deep learning, to code clone detection and authorship attribution represents a significant advancement in the field of software analysis. These approaches offer the potential to capture complex patterns and similarities in code that may be difficult to detect using traditional rule-based or heuristic methods.

[145] use of recurrent neural networks (RNNs) for authorship attribution is particularly noteworthy. By representing code samples as one-step sequences using TF-IDF (Term Frequency-Inverse Document Frequency), they've created a method that can potentially capture both the structure and content of code in a way that's amenable to deep learning analysis. RNNs are well-suited for processing sequential data, making them a natural choice for analyzing code, which has an inherent sequential nature. This approach could be especially powerful in detecting subtle patterns in coding style that might be indicative of a particular author, even when deliberate attempts have been made to obfuscate authorship.

The work of [146] on using Abstract Syntax Tree (AST) features for authorship identification represents a hybrid approach that combines traditional software

engineering techniques with machine learning. By extracting manually crafted features from ASTs, they're leveraging deep structural information about the code.

This method could be particularly effective at capturing stylistic choices that manifest in the code's structure, such as preferences for certain control structures or code organization patterns. The use of machine learning on these features allows for the discovery of complex relationships that might not be apparent through manual analysis.

[147] researchers introduced an innovative approach by building Markov chain models from ASTs. This method combines the structural information captured by ASTs with the probabilistic modelling power of Markov chains. By doing so, it can potentially capture both the static structure of the code and patterns in how that structure typically evolves or varies. This could be particularly useful for detecting semantic clones that have similar functionality but different surface-level implementations.

While these machine learning-based approaches show great promise, it's important to acknowledge their limitations, including too much reliance on manually crafted features: As pointed out, methods that depend heavily on hand-engineered features can be labor-intensive to develop and may not generalize well to different programming languages or coding styles. This limitation highlights the need for more end-to-end learning approaches that can automatically extract relevant features from raw code. Many machine learning models, especially deep learning models, can be computationally intensive to train and apply to large codebases. This can limit their practicality in real-world software development environments where quick, on-the-fly analysis is often needed. Deep learning models, in particular, often act as "black boxes," making it difficult to understand exactly why they've classified two code segments as clones or attributed authorship in a certain way. This lack of interpretability can be a significant drawback in contexts where explanations for decisions are necessary. Machine learning models typically require large amounts of training data to perform well. In the context of code clone detection or authorship attribution, obtaining sufficiently large and diverse datasets of labelled code can be challenging.

Some machine learning approaches may be sensitive to superficial code changes, such as variable renaming or code reformatting, which shouldn't affect the determination of

clones or authorship. Despite these limitations, the potential of machine learning- based approaches in this field is significant; especially it is used with methods such as AST

Visualisation methods for code clone detection and pattern analysis have emerged as an innovative approach to understanding and managing code similarities in software repositories. These techniques leverage the power of human visual perception to identify patterns and anomalies that might be challenging to detect through purely algorithmic means.

One particularly intriguing method involves converting source code into grayscale images. This approach transforms the ASCII decimal values of each character in the source code into a square matrix, which is then rendered as a grayscale image. Each pixel in the resulting image corresponds to a decimal value from the original code sequence, with grayscale values ranging from 0 to 255. This visual representation allows for a unique perspective on code structure and composition, enabling developers and analysts to visually compare different code fragments and potentially identify similarities or differences that might not be immediately apparent in textual form. The power of this method lies in its ability to compress large amounts of code information into a compact, visually digestible format, potentially revealing patterns or structures that might be obscured in traditional text-based representations.

Another significant development in this field is the EgyCD [148] code clone detection, which is based on sequential pattern mining. While specific details about its visualisation techniques are limited in the available search results, the integration of visualisation into a pattern mining-based clone detector suggests a promising direction for enhancing the interpretability and usability of clone detection results. By providing visual representations of detected clones, EgyCD likely aims to make it easier for developers to understand and act upon the identified code similarities.

The application of visualization techniques to facilitate clone detection across different software versions represents another important area of research. While the exact methods employed are not specified in the search results, this approach acknowledges the dynamic nature of software development and the need to track how code clones evolve over time. Visualizing clones across versions could potentially help developers

understand the propagation of code duplication throughout a project's lifecycle, informing decisions about refactoring of code consolidation.

These visualization approaches, while diverse, share a common goal of making code clone information more accessible and actionable for developers and analysts. By translating complex code relationships into visual formats, these methods aim to leverage human visual processing capabilities to complement algorithmic analysis. This synergy between computational analysis and visual interpretation has the potential to enhance our understanding of code structures and similarities in ways that purely textual or numerical representations might not achieve.

However, it's important to note that the effectiveness of these visualization techniques likely depends on various factors, including the scale of the codebase, the specific types of clones being sought, and the familiarity of users with the visualization methods. Furthermore, while visualization can be a powerful tool for pattern recognition, it may need to be combined with more traditional analytical methods to provide a comprehensive understanding of code clone phenomena.

As research in this area progresses, we might expect to see more sophisticated visualisation techniques that can handle larger codebases, represent more complex clone relationships, and perhaps even incorporate interactive elements to allow developers to explore and manipulate clone data in real-time. The integration of machine learning techniques with visualisation could also lead to more adaptive and insightful visual representations of code similarities.

This approach is simple and easy to implement. By bridging the gap between algorithmic analysis and human intuition, this approach has potential to significantly enhance our ability to understand, manage, and leverage code similarities in increasingly complex software systems. As the field evolves, we can anticipate further innovations that will continue to push the boundaries of how we visualise and interact with code clone information.

Table 2.1: Tabular Summary of Main Works Discussed

Author(s)	Year	Method/Approach	Key Findings	Strengths	Weaknesses
Baxter et al.	1998	Lexical vs. Syntactic (AST) Analysis	Lexical analysis provides a crude overview; AST reveals duplicated subroutines more precisely	Efficiency of lexical analysis for initial scans	Lexical may miss structural similarities, AST more computationally intensive
Greenan	2010	Method-level Code Clone Detection on Transformed ASTs	Transformed ASTs increase efficiency and Accuracy for Method level detection	Enhanced effectiveness of clone detection at method level	Computational complexity, variability with programming languages
Zou et al.	2020	Graph Theory and Machine Learning (CCGraph)	Improved accuracy and efficiency in code clone detection	Use of PDGs and WL graph kernel captures semantic properties	Complexity of setup, validation Across languages needed
Sajnani et al.	2016	Token-based Clone Detection (SourcererCC)	Scalable solution using locality sensitive hashing	High precision and recall	Limited to exact and near-miss clones, doesn't detect complex semantic clones
Gabel et al.	2008	Token-based Clone Detection (CCFinder)	Uses suffix arrays for improved efficiency	Versatility in detecting various clone types	May miss clones with significant structural differences
Zheng et al.	2020	AST-based Plagiarism Detection (CodEX)	High accuracy in plagiarism detection with AST based methods	Robustness against obfuscatin attempts	Computational complexity, especially for large codebases
Devi and Punithavalli	2011	Comparative Analysis of Various Clone Detection Techniques	Hybrid approach combining multiple techniques suggested	Versatility and comprehensive detection	Computational expense and large search spaces
Kim et al.	2011	Abstract Memory State Comparison (MeCC)	Detects semantic clones by comparing abstract memory states	Deep analysis of code behaviour	Resource-intensive, scalability issues

Schugerl et al.	2020	Feature Vector-based Semantic Clone Detection	Uses data types, control blocks, and method calls as features	Captures key aspects of code functionality	Increased computationl complexity
Almori and Stephan	2021	Code Slicing for Semantic Clone Detection (SrcSlice)	Two-stage clustering approach isolates functionally relevant parts of the code	Focused analysis of code behavior	Potentially resource-intensive

In summary, this chapter found following methods work well in code detection domain:

1. **Lexical Analysis Efficiency**: Lexical analysis is efficient for broad, initial scans of large codebases, making it a suitable first step in a multi-stage clone detection process.

2. **AST-based Precision**: AST-based approaches offer greater precision, particularly for identifying complex structural similarities and for fine-grained refactoring efforts.

3. **Hybrid Approaches**: Combining multiple techniques, such as lexical for initial scans and AST for detailed analysis, provides a more comprehensive clone detection solution.

4. **Graph-based Methods**: Graph-based techniques like CCGraph show promise in capturing semantic relationships, though they introduce complexity in setup and use.

Machine Learning Integration: The application of machine learning, particularly deep learning, enhances the ability to detect complex and semantic clones, though it requires significant computational resources and large training datasets. However, it was also found that the machine learning approach needs integration, or combination approaches such AST to cover up code pieces at fine - grain level.

Chapter-3

METHODOLOGY

In this chapter, explanations regarding how the research objectives were achieved can be found in a systematic manner. The chapter has four sections. The first section gives a comparative view of the contemporary methods of detecting code cloning (meta-analysis). The second section discusses a proposal of a novel approach to overcome the challenges and issues found in literature surveys and formulated in the problem statement. The next section discusses the implementation of the proposal of the clone detection algorithm from the previous and the chapter ends with the summary of the steps taken to obtain all the research objectives.

3.1 Foundational Background

The phenomenon of code cloning, which involves the replication of code fragments within a given software system, has garnered considerable interest owing to its implications for software quality and maintainability. The identification and handling of code clones have become a critical concern for software developers and researchers due to the redundancy and heightened complexity they introduce to software systems. The objective of this literature review is to investigate current scholarly research on algorithms and techniques for code cloning, with the aim of offering an understanding of the progress achieved in this area. Hence, in this section, the purpose of this discourse is to furnish a comprehensive exposition of code cloning and its ramifications in the realm of software engineering. The present survey aims to provide a thorough comprehension of code cloning, encompassing its definition, categorizations, and probable implications on software quality characteristics such as maintainability, readability, and comprehensibility.

The objective is to conduct a comprehensive analysis of contemporary techniques and algorithms for detecting code cloning. The present study aims to investigate the extant body of literature to ascertain and scrutinize diverse techniques for detecting code cloning, which encompass token-based, abstract syntax tree (AST)-based, metric-based, and hybrid approaches. The primary objective is to comprehend the potential

advantages, drawbacks, and efficacy of these methodologies in detecting and handling code duplications. The second objective is to analyse the metrics and evaluation techniques employed in studies related to code cloning. The present study aims to examine the metrics utilised in the assessment of code cloning detection algorithms. These metrics include precision, recall, F-measure, and detection rates. The objective is to ascertain prevalent evaluation methodologies and obstacles encountered in the appraisal of the efficacy of code duplication detection techniques. The third objective is to discern nascent patterns and obstacles in the domain of code duplication investigation. The survey aims to investigate current research endeavours in order to identify emerging trends. These trends include the detection of fine-grained and Type 3 clones, the detection of clones in contemporary programming paradigms (such as functional programming and machine learning), and techniques for managing code clones.

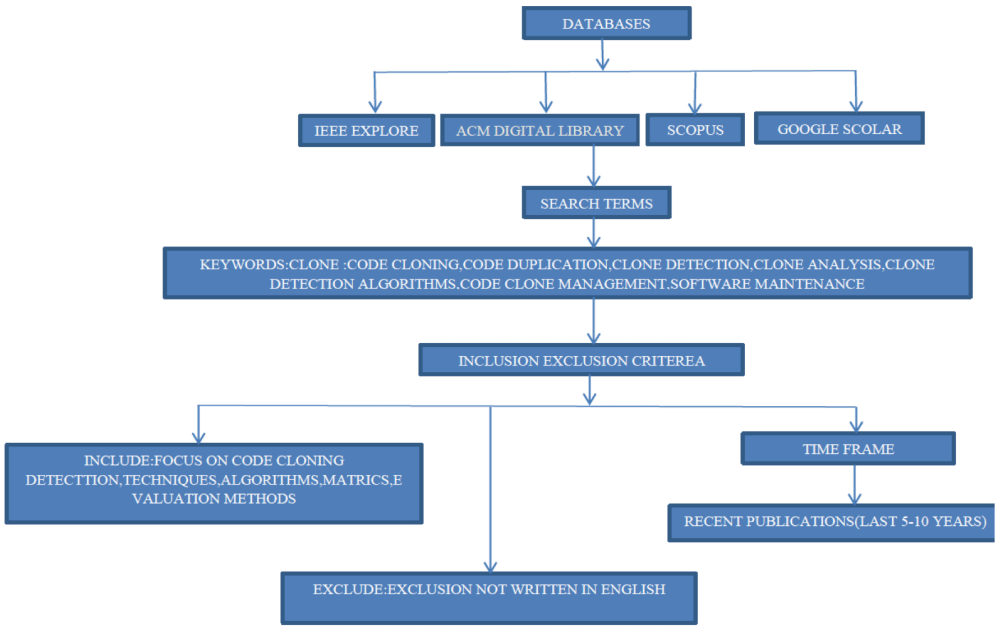


Figure 3.1 Methodology for Meta-Analysis

To identify relevant research articles for this literature survey on code cloning algorithms and methods, the following search strategy will be employed:

1. Databases: Conduct a comprehensive search across multiple academic databases, including IEEE Xplore, ACM Digital Library, Scopus, and Google

Scholar. These databases cover a wide range of computer science and software engineering literature.

2. Search Terms: Utilise a combination of relevant keywords and phrases to capture articles related to code cloning algorithms and methods. The search terms may include "code cloning," "code duplication," "clone detection," "clone analysis," "clone detection algorithms," "code clone management," and "software maintenance."

3. Inclusion/Exclusion Criteria: Apply specific inclusion and exclusion criteria to select relevant articles. Include articles that focus on code cloning detection techniques, algorithms, metrics, and evaluation methods. Exclude articles that are not written in English or do not meet the relevance criteria.

4. Time Frame: Limit the search to recent publications, considering articles published within the last 5 to 10 years. This timeframe will ensure the inclusion of contemporary research work and capture the latest advancements in code cloning algorithms and methods.

Combining search terms with Boolean operators (AND, OR) and applying them to the aforementioned databases constitutes the search strategy. The initial search will yield a large number of articles, which will be narrowed down by filtering titles, abstracts, and full-text articles based on inclusion/exclusion criteria. By employing this search strategy, a comprehensive collection of relevant research articles on code cloning algorithms and methods will be identified, allowing for a comprehensive examination of the topic in the literature review.

3.2 Comparative Analysis of Recent Works

From the search phases as we move towards the analysis of the research works, it was found that understanding is relatively simple in Token-Based methods due to their intuitive character, as they rely on lexical similarities between code fragments. When attempting to comprehend them, they are, however, typically not opaque. In addition, contemporary literature demonstrates that this is because token-based analysis is founded on surface-level lexical information. The interpretability of token-based

methods is limited because they concentrate on token-level matching rather than capturing higher-level structural information of the code fragment they are analysing.

Since token-based methods predominantly involve token comparison and matching, they typically have low computational overhead. For more details, Table 3.1 may be referred to.

Table 3.1: Comparative analysis of code clone Techniques.

Method Category	Advantages	Limitations	Ease of Understanding	Opacity	Interpretability	Computational Overhead
Token-Based	- Simple and intuitive approach	- May suffer from high false positive rate	High	Low	High	Low
AST-Based	- Captures structural similarities	- Requires complex parsing and AST analysis	Moderate	Moderate	Moderate	Moderate
Metric-Based	- Quantitative measure of code similarity	- Limited to specific metric definitions	Moderate	Moderate	Moderate	Low to Moderate
Hybrid	- Combines strengths of multiple methods	- Increased complexity and implementation	Moderate to High	Moderate	Moderate to High	Moderate to High
Machine Learning	- Can handle large and complex codebases	- Requires labelled training data	Moderate to High	High	Low to Moderate	Moderate to High
Deep Learning	- Can capture intricate patterns and features	- Requires substantial computational resources	Low to Moderate	High	Low	High

Due to the need for knowledge of abstract syntax trees and parsing techniques, AST-based methodologies may have a steeper learning curve. Due to the intricate tree- based

representations, operations, and transformations of the code data, AST-based methods can have a moderate degree of opacity.

The interpretability of AST-based methodologies can vary depending on the complexity of the AST analysis techniques employed. Due to the parsing and analysis of AST structures, AST-based methods typically have a higher computational overhead, as demonstrated by numerous studies. It has been discovered, however, that they are useful for storing code data for improved granule level analysis.

Metric-based code clone detection strategies are typically simple to comprehend, as they involve defining and calculating quantitative metrics to measure code similarity. Due to their emphasis on mathematical calculations and numerical comparisons, Metric-based methods typically have a low opacity level. The interpretability of these methods is limited, as they rely predominantly on quantitative measures without capturing structural or semantic information. However, with a few enhancements, structural information can be captured. Using a combination of AST and metric approach, for instance, both structure and quantitative measures can be assessed. Hence, in many cases Hybrid methods may be better; however, they can vary in terms of ease of understanding, as they combine different approaches, potentially introducing additional complexity. Naturally, the opacity of hybrid methods will vary depending on the constituent methods integrated and their individual characteristics. Interpretability can be moderate in hybrid methods, as it depends on the combined features and techniques employed. Hybrid methods may have varying computational overhead, influenced by the complexity and computational requirements of the integrated methods.

Compared to deep learning approaches, machine learning-based approaches can have a moderate to steep learning curve due to the need to comprehend complex algorithms and models. Methods for machine learning can manifest varying degrees of opacity, especially deep learning models, which are notoriously opaque. In machine learning methods, especially deep learning models, interpretability can be limited, making it difficult to comprehend the decision-making process. As a result of their computational requirements, machine learning methods may have moderate to high computational

overhead, particularly in deep learning models. Due to the complexity of their architectures and training procedures, deep learning methods can have a precipitous learning curve. As they entail multiple layers of interconnected neurons and complex feature representations, deep learning models are often characterised by their high opacity.

The interpretability of deep learning models is typically low, as their decision-making processes are difficult to interpret and explain. Deep learning techniques are computationally intensive and costly, necessitating substantial computational resources and extended training durations. Hence,

3.3 Adaptive Prefix Filtering for Accurate Code Clone Detection in conjunction with Meta-Learning

From **meta-analysis, we can conclude following:**

- **There is no single way to solve this problem:** Understand and insights gained clearly point out that there's no single perfect method for code clone detection, especially for fine-grained clones (very similar code snippets). This implies traditional techniques like simple string matching might not suffice.
- **Focus Areas:** The research identifies two crucial aspects for improvement:
- **Structure of the Code (soc):** This likely refers to analysing the code's organization, like control flow, loops, function calls, and nesting. Capturing these structural similarities is essential for identifying clones beyond just surface-level text.
- **Qualitative Properties of the Code (qpc):** This could encompass factors like variable names, function names, comments, and data types. These qualitative aspects can provide clues about the code's purpose and functionality, aiding in clone detection.

Hence, there a need for better approach that can do the following:

- **Prefixing and Feature Extraction:** Inferences and analysis in this context suggests that using prefixes while iterating through the code structure (**soc_f**) offers more discriminating power than traditional approaches. This implies

techniques like prefix trees or n-grams might be employed to extract informative features from the code's structure.

- **Qualitative Features (qpc_f):** These features, likely derived from the code's qualitative properties, are expected to add reliability to the overall feature set. This strengthens the idea that both structural and qualitative analysis are important.

Hence, there is a need for a building a code clone detection Meta-Classifier:

- **Classifier Challenges:** Hence, there is an urgent need to acknowledge the difficulty of constructing a single, perfect classifier (CCL) for code clone detection. This suggests that existing classifiers might have limitations.
- **Stacking Architecture (SA):** Consequently, it is proposed that a novel approach – a stacking architecture (meta-classifier) that combines multiple existing classifiers (CCL_1, ..., CCL_n). By combining the outputs of these individual classifiers, the meta-classifier aims to achieve higher accuracy (ACC) than any single classifier alone.

The novel stacking architecture is justified by acknowledging that current code clone detection methods struggle specifically with fine-grained clones, which are similar code snippets containing subtle variations. To overcome this limitation, the hypothesis proposes an enhanced feature extraction approach, suggesting that applying prefixes while iterating through the code structure (referred to as soc_f) can capture more discriminative features than relying on traditional Abstract Syntax Trees (ASTs) alone. This methodology implies the use of techniques like n-grams or prefix trees to glean more informative details about the code's organization. Additionally, the research emphasizes the importance of Qualitative Features (qpc_f), extracted from code properties such as variable names, function names, comments, and data types, which are expected to add significant reliability to the overall feature set. Finally, the approach incorporates the established concept that a stacking architecture (meta-classifier) can combine multiple individual classifiers to potentially improve the overall accuracy in clone

The approach will include two-pronged approach for improved code clone detection for the solving the issues rose in problem statement and hypothesis:

1. **Feature Extraction:** By leveraging code structure and qualitative properties, researchers aim to extract more informative features (soc_f and qpc_f).

Meta-Classifier Design: A stacking architecture that combines multiple existing classifiers is proposed to potentially achieve higher accuracy than any single classifier.

3.4 Ensemble Architecture Design and Optimization

This section explains the Architectural design of the solution and hypothesis, its rationale, and the planned evaluation method in more detail. The main hypothesis is that a novel stacking architecture (SA) that combines multiple existing code clone detection classifiers (CCL_1, CCL_2, ..., CCL_n) can achieve higher accuracy (ACC) in detecting code clones, particularly at the fine-grained level.

3.4.1 How the hypothesis is tested in this research:

- **Data Collection:**

A comprehensive dataset of code clones were assembled, encompassing both fine-grained and coarse-grained clones. This is crucial to ensure the stacking architecture can handle different levels of similarity. The representativeness of the dataset is vital. An unbalanced or biased dataset with an overabundance of a specific type of clone could skew the results. Techniques for creating a balanced and diverse dataset will be employed.

2. Classifier Training:

- Multiple existing code clone detection classifiers (CCL_1, CCL_2, ..., CCL_n) will be trained on the prepared dataset. This involves selecting a variety of established classifiers with different strengths and weaknesses.

3. Stacking Architecture Implementation:

- The stacking architecture (SA) will be designed to combine the predictions from

the individual classifiers. This involves choosing an appropriate stacking approach (e.g., weighted majority voting) and integrating the classifiers within the architecture.

4. **Accuracy Evaluation:**

- The accuracy (ACC) of the stacking architecture will be measured on a held-out test set. This test set will be separate from the training data to ensure unbiased evaluation.

5. **Outcome Analysis:**

- If the results support the hypothesis ("H"), it implies that the stacking architecture can be a valuable tool for improving code clone detection accuracy in real-world applications. The research acknowledges potential challenges that might surface during testing:

3.4.3 Key Challenges :

Following Challenges have been undertaken:

- **Dataset Comprehensiveness:** Collecting a dataset that accurately represents real-world code with a good balance of fine-grained and coarse-grained clones can be difficult due to the vast diversity of codebases. Strategies for creating a representative dataset will be crucial.
- **Classifier Effectiveness:** The individual effectiveness of the chosen classifiers (CCL_1, CCL_2, ..., CCL_n) could vary. This variation could potentially impact the overall accuracy of the stacking architecture. Careful selection of classifiers with complementary strengths will be important.
- **Integration and Compatibility:** Integrating and ensuring compatibility of different classifiers within the stacking architecture (SA) could pose challenges. Techniques for addressing compatibility issues will be explored.

By addressing these challenges and conducting a thorough evaluation, the research aims to validate the hypothesis and establish the effectiveness of the stacking architecture for

improved code clone detection. Based on the above, meta-analysis, Hypothesis formulated and problem statement, here are the detailed steps with the objectives were obtained and validation of the work was done. In the next section we explain the algorithm but, before that information, the dataset is shared.

3.4.4 Data Characteristics:

The dataset for this project is entirely sourced from GitHub, the world's largest platform for hosting and collaborating on code. To gather relevant and high-quality code samples, we developed an automated data collection script that programmatically searches for and retrieves repositories based on specific criteria. The script uses GitHub's search functionality to find repositories matching the query "python cli" or "Java cli" to focus on command-line interface projects, which typically contain well-structured, executable code examples. We further filter results to include only Python language projects that have achieved significant community recognition, specifically those with more than 50 stars, as this popularity threshold generally indicates code that follows good practices and has undergone community review.

Once potential repositories are identified through the search, the script clones the top repositories sorted by their star count, downloads their complete codebase, and systematically extracts the content from all Python files (files with the .py extension) within these repositories. This process results in a dataset composed of source code from diverse open-source Python command-line interface projects, representing various coding styles, problem domains, and implementation approaches that real developers use in practice. The dataset's scope includes everything from simple utility scripts to complex application codebases, providing a rich collection of code examples for analysis.

Regarding dataset size, it's important to note that our collection is dynamic rather than fixed. The exact volume of data depends on a configurable parameter called max_repos in our collection script, which determines how many repositories we download and process. By default, this parameter is set to 20, meaning the script will clone and analyze the 20 most popular repositories matching our criteria. This flexible approach allows us to easily scale our dataset up or down based on computational resources and research

needs, from analyzing just a few repositories for preliminary experiments to processing hundreds of repositories for comprehensive studies. The variable nature of the dataset ensures we can balance depth of analysis with breadth of examples according to the specific requirements of each phase of our clone detection research.

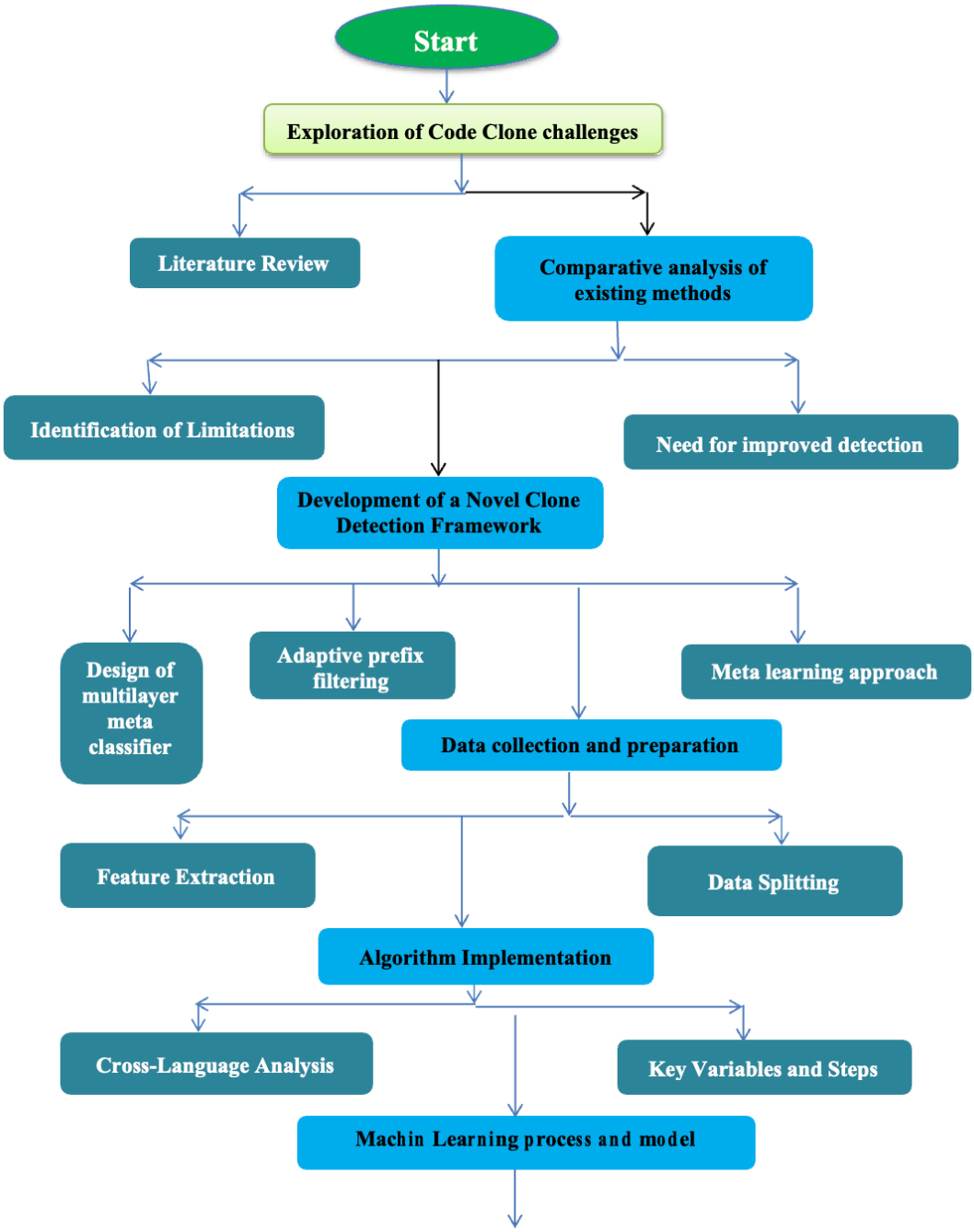
3.5 Proposed Algorithm

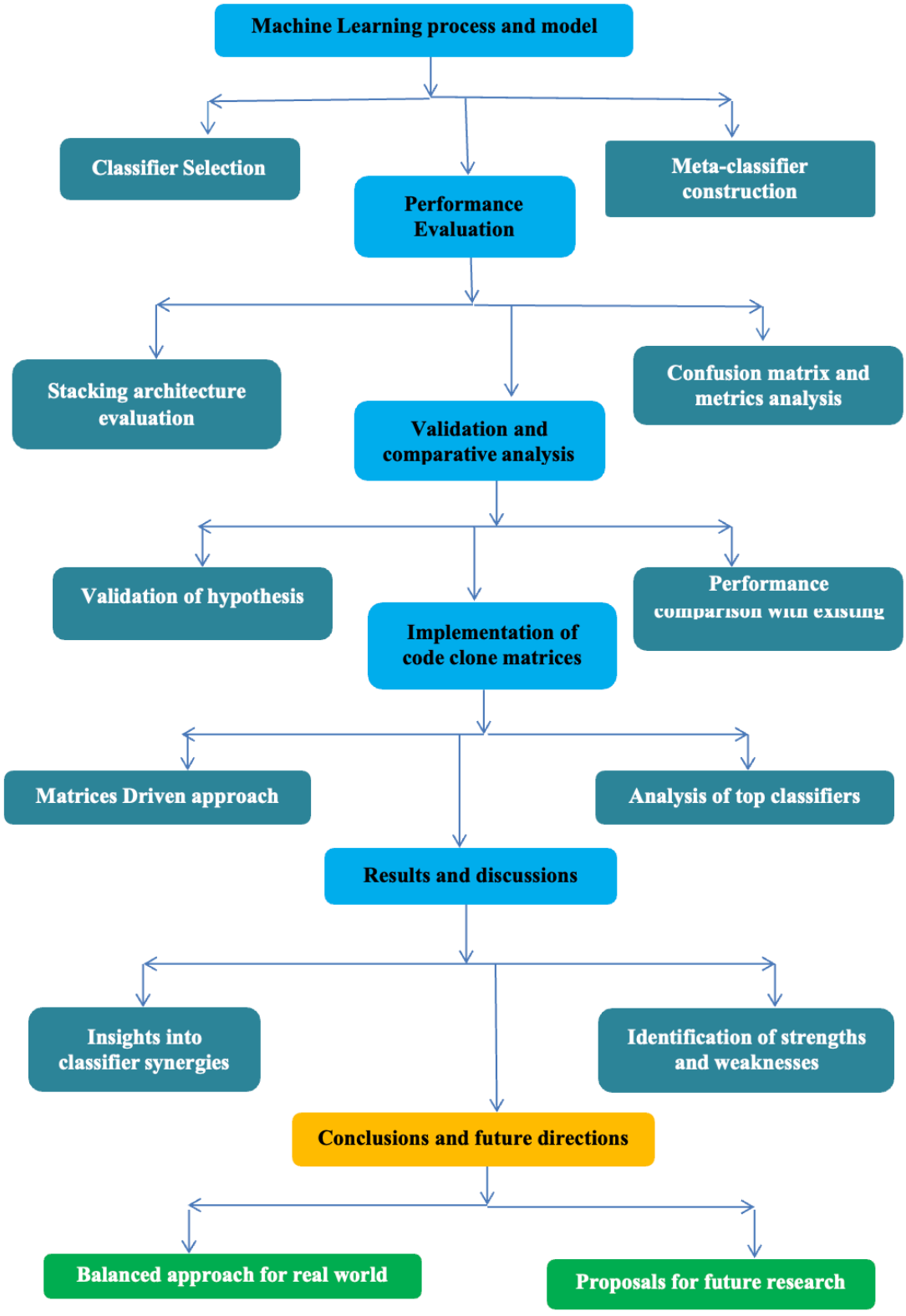
The Code listing as stated below shows a function named Collect Code Structure. This function is to analyze the structure of source code from a Python or Java file. It processes the code into individual tokens, extracts pertinent information about these tokens, and stores this information in a structured DataFrame. The DataFrame will include the token itself, its type, line number, and the programming language of the source code. Along with all these facilities the function incorporates a mechanism to detect abstract prefixes in the code tokens.

```
Proposed Algorithm :
FUNCTION CollectCodeStructure(file
path: String) → DataFrame INPUT: file
path: Path to the Python or Java source
code file OUTPUT: A DataFrame
containing the code structure

1: BEGIN

2: // Read the content of the file specified by file path into a
variable named 'code'
3: code ← READ FILE (file path)

4: // Split 'code' into individual tokens

5: tokens ← SPLIT code INTO INDIVIDUAL TOKENS

6: // Create an empty data structure, 'df', to store the code structure

7: df ← NEW DATAFRAME with columns ("token",
"type", "line number", "language")

8: // For each token in tokens, extract its type and
determine its line number

9: FOR EACH token IN tokens DO

10:     type ← EXTRACT TYPE FROM token
```

```
11:      line number ←
DETERMINE LINE NUMBER OF
token

12:      APPEND (token, type, line
number) to df

13: // Determine the language of the source
code file and add it to 'df'

14: IF file path ENDS WITH ".py" THEN


15:      ADD "python" TO df's "language" COLUMN

16: ELSE IF file path ENDS WITH ".java" THEN

17:      ADD "java" TO df's "language" COLUMN

18: // Incorporate Abstract Prefix Filtering

19: // Create a set of unique abstract prefixes from the tokens

20: abstract prefixes ← NEW SET

21: FOR EACH token IN tokens DO

22:      prefix ← EXTRACT PREFIX FROM token

23:      ADD prefix TO abstract prefixes

24: // For each row in 'df', check if any abstract prefix is a part of its token

25: FOR EACH row IN df DO

26:      FOR EACH prefix IN abstract prefixes DO

27:        IF prefix EXISTS IN row's token, THEN

28:          SET row's "abstract prefix" TO prefix

29:  RETURN df

30: END FUNCTION
```

Flow Chart for Proposed Algorithm




Machine Learning process and model
Classifier Selection
Performance Evaluation
Meta-classifier construction
Stacking architecture evaluation
Validation and comparative analysis
Confusion matrix and metrics analysis
Validation of hypothesis
Implementation of code clone matrices
Performance comparison with existing
Matrices Driven approach
Analysis of top classifiers
Results and discussions
Insights into classifier synergies
Identification of strengths and weaknesses
Conclusions and future directions
Balanced approach for real world
Proposals for future research

3.5.1 The Key Variables Involved in the Algorithm

1. **file path**: The path to the source code file to be analyzed.
2. **code**: The content of the source code file.
3. **tokens**: The individual tokens parsed from the source code.
4. **df**: A DataFrame to store the code structure, including token, type, line number, and language.
5. **type**: The type of each token.
6. **line number**: The line number where each token is found.
7. **abstract prefixes**: A set of unique abstract prefixes extracted from the tokens.
8. **prefix**: A specific prefix part of a token.

3.5.2 Steps of the Proposed Algorithm

1. **Read File Content**: The algorithm starts by reading the content of the specified file path into the variable code. This is essential to access the source code for processing.

2. **Tokenize Code**: The source code is split into individual tokens. Tokenization is crucial for analysing the syntactic elements of the code.

3. **Initialize DataFrame**: An empty DataFrame df is created with columns for token, type, line number, and language. This structure will help organize and store the extracted information.

4. **Extract Token Details**: For each token, the algorithm extracts its type and determines its line number. These details are appended to the DataFrame, building a structured representation of the code.

5. **Determine Language**: The algorithm identifies the programming language of the source code based on the file extension. This information is added to the DataFrame.

6. **Abstract Prefix Filtering**: The algorithm identifies and processes abstract prefixes from the tokens. This step involves:

- Creating a set of unique abstract prefixes.

Checking if any abstract prefix is a part of each token in the DataFrame.

- Updating the DataFrame to include the abstract prefix for relevant tokens.

3.5.3 Key Advantages of the design of Algorithm

1. **Structured Representation**: By converting the source code into a DataFrame, the algorithm provides a structured and easily manipulable representation of the code structure.
2. **Language Detection**: Automatic identification of the programming language helps in tailoring further analysis or processing specific to Python or Java.
3. **Abstract Prefix Analysis**: Incorporating abstract prefix filtering can be beneficial for various code analysis tasks, such as identifying patterns or performing semantic analysis.

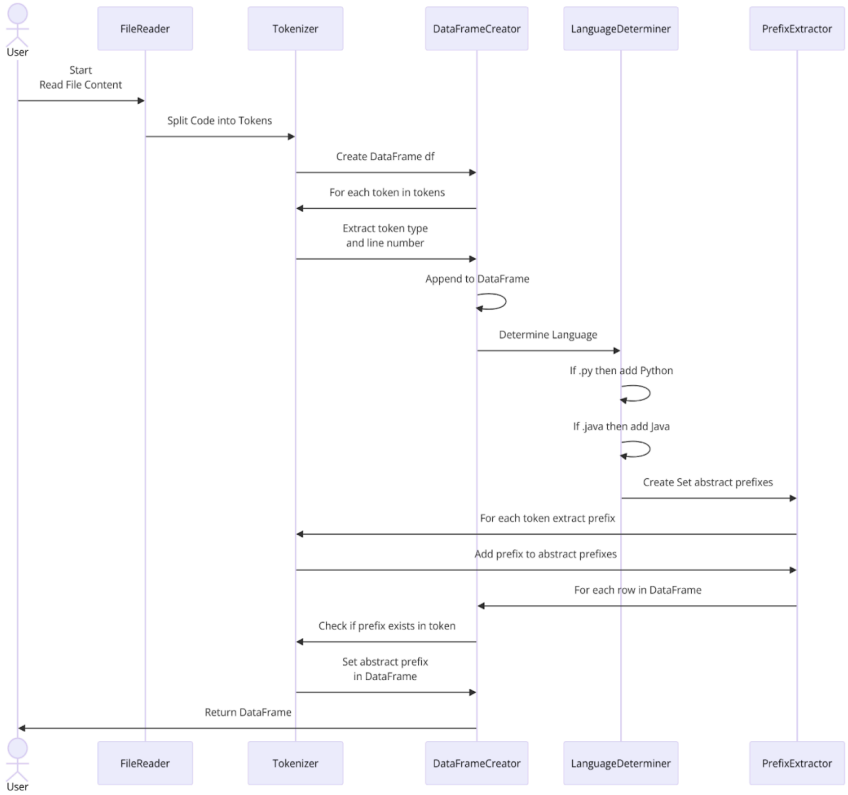


Figure 3.2 Process for Analysis Code Files

This algorithm described in the figure 3.2 is a process for analysing code files. It begins with a user initiating the process through a FileReader, which reads the content of a file. The content is then passed to a Tokenizer that splits the code into individual tokens. A DataFrameCreator takes these tokens and creates a DataFrame structure, extracting information such as token type and line number for each token. The LanguageDeterminer then analyzes the tokens to identify the programming language used (e.g., Python or Java). Next, a PrefixExtractor creates a set of abstract prefixes based on the identified language. The algorithm then iterates through each token, extracting and adding relevant prefixes to the set of abstract prefixes. Finally, it processes each row in the DataFrame, checking if the token contains any of the identified prefixes and updating the DataFrame accordingly. The result is a structured DataFrame containing detailed information about the code's tokens, their types, locations, and abstract representations, which is then returned to the user for further analysis or processing. For example, for a code such as Code Listing below:

```
  def greet(name): print(f"Hello, {name}!")
greet("Alice")
```

1. The User initiates the process, and the FileReader reads this Python file's content.
2. The Tokenizer splits the code into tokens: ['def', 'greet', '(', 'name', ')', ':', 'print', '(', 'f"Hello, {name}!"', ')', 'greet', '(', '"Alice"', ')']
3. The DataFrameCreator creates a DataFrame with these tokens, adding information like token type and line number:

Table 3.2: Token classification

Token	Type	Line
def	keyword	1
greet	identifier	1
(	punctuation	1
name	identifier	1
)	punctuation	1
:	punctuation	1
print	built-in	2
...	...	...

4. The LanguageDeterminer analyses these tokens and identifies the language as Python based on keywords like 'def' and the syntax.

5. The PrefixExtractor creates a set of abstract prefixes for Python, which might include things like 'def_' for function definitions.

6. The algorithm then iterates through each token, extracting relevant prefixes. For example, 'greet' might be identified as a function name and given the prefix 'func_'.

7. Finally, it processes each row in the DataFrame, checking for these prefixes. The 'greet' identifier would be updated with its abstract prefix:

Table 3.3:

Abstract Prefix generation

Token	Type	Line	Abstract Prefix	Language
def	keyword	1	-	py
greet	identifier	1	func_	py
...	...	...	...	

8. The resulting DataFrame, now enriched with abstract representations of the code elements, is returned to the User for further analysis or processing.

9. This process transforms the raw code into a structured format thatS captures both the syntactic elements and higher-level abstractions, facilitating various forms of code analysis.

Further, this function iterates through all the code files from multiple repositories. As depicted in Algorithm 1 a set of abstract prefixes were generated using adaptive prefix filtering and for each token was stored in data structure (soc f). An abstract prefix is a sequence of consecutive alphanumeric characters in a token. The algorithm code creates an additional column in the data structure f soc to store the abstract prefixes. The ’abstract prefix’ column contains the abstract prefix of each token.

Table 3.4: Code Clone metrics

S. No	Metric	Description	Variable	Sample Values
1	LOC	Lines of code	num_loc	100, 150, 80, 200, 120
2	Avg. Function Length	Average number of lines per function	num_function / num_func	10.5, 8.2, 12.3, 9.8, 11.1
3	LCC	Lines of code in the longest function	num_lcc	50, 40, 60, 45, 55
4	Total Lines	Total number of lines in the code file	num_line	300, 250, 400, 350, 275
5	Comment Lines	Number of lines with com- ments	num_com	20, 15, 25, 18, 22
6	Classes	Number of classes in the code file	num_cls	5, 3, 4, 6, 2
7	Loops	Number of loops in the code file	num_lops	10, 8, 12, 9, 11
8	Functions	Number of functions in the code file	num_func	15, 12, 18, 14, 16
9	Conditionals	Number of conditionals in the code file	num_cond	25, 20, 30, 22, 28
10	Total Words	Total number of words in the code file	num_word	500, 450, 550, 480, 520
11	Total Characters	Total number of characters in the code file	num_chac	2500, 2000, 2800, 2300, 2600
12	Average Line Length	Average length of each line	num_chac / num_line	8.3, 7.5, 9.1, 8.7, 8.2
13	Average Word Length	Average length of each word	num_chac / num_word	5.0, 4.4, 5.2, 4.8, 5.1
14	Comment to Code Ratio	Ratio of comments to code lines	num_com / num_loc	0.2, 0.15, 0.18, 0.22, 0.19
15	Cyclomatic Com- plexity	Measure of code complexity	num_cyc	8, 6, 10, 7, 9
16	Special Characters	Number of special characters in the code file	num_sp	30, 25, 35, 28, 32
17	Imports	Number of import statements in the code file	num_import	5, 4, 6, 3, 7

The Abstract Syntax Tree (AST) is a powerful algorithm in the field of static code analysis, particularly for tasks like code clone detection. Its primary advantage lies in its ability to represent the structural essence of code, regardless of the programming language, by decomposing it into a hierarchical tree of its fundamental components. When a piece of code is parsed into an AST, it undergoes a transformation that strips away surface-level details while preserving the core logic and structure. In this work, our focus is python and java, and the work can be modified for expanding to more languages. The modified function will be primarily replacing the current language-specific parsing module (such as Python's ast) with a **universal parser like tree-sitter.**

This process involves breaking down the code into its constituent parts:

1. Statements: These are the individual instructions or commands in the code.

2. Expressions: These are combinations of values, variables, operators, and function calls that produce a value.

3. Operators: These are symbols or keywords that perform operations on one or more operands.

4. Control structures: These include loops, conditionals, and other constructs that dictate the flow of execution.

5. Function and class definitions: These represent the organisational units of code.

By focusing on these essential elements, the AST provides a more abstract and semantically rich representation of the code than the raw text. This abstraction is particularly valuable for code clone detection because it allows for the identification of structural similarities even when superficial differences exist. Some key benefits of using ASTs for clone detection include:

1. Refactoring resilience: ASTs can detect clones despite common refactoring changes such as:

    - Variable and function renaming
    - Code reformatting (changes in whitespace, line breaks, etc.)
    - Statement reordering within a block (when order doesn't affect semantics)

2. Language independence: While the specific structure of an AST may vary between programming languages, the concept is universal, allowing for cross-language clone detection techniques.

3. Semantic analysis: ASTs facilitate deeper semantic analysis, enabling the detection of Type-2 (syntactically similar) and Type-3 (semantically similar) clones.

4. Efficiency: Comparing ASTs can be more efficient than comparing raw code text, especially for large codebases. Example, how it has been done in our case,

```python
def factorial(n): result = 1
for i in range(1, n+1): result *= i
return result
```

```
        def fact(num): acc = 1
                for j in range(1, num+1): acc *= j
        return acc
```

Despite the apparent differences in these functions (variable names, formatting), their ASTs would reveal nearly identical structures:

1. Both have a function definition node at the root.
2. Each contains an assignment statement initialising a variable to 1.
3. Both have a for loop with a range from 1 to n+1 (or num+1).
4. Inside the loop, there's a multiplication assignment operation.
5. Finally, both end with a return statement.

Our AST-based clone detection algorithm recognizes these structural similarities and identifies these functions as clones, even though a simple text-based comparison might not. It's worth noting that while ASTs are powerful, they're not without limitations. They may not capture certain types of clones, such as those with significant structural differences but similar functionality (Type-4 clones). Additionally, building and comparing ASTs can be computationally expensive for very large codebases.

3.6 Collection of Qualitative Features of Code Files (QPC)

The dataset used for this code clone analysis is a comprehensive collection of qualitative features extracted from code files, referred to as QPC (Qualitative Features of Code). This dataset represents a significant effort to quantify and categorize the characteristics of code that may indicate cloning or duplication. The dataset comprises 17 distinct code clone metrics [see table 3.4], carefully selected to capture various aspects of code similarity and structure.

3.6.1 Data Preparation and Splitting

The use of stratified sampling for splitting the dataset into training and testing sets is a crucial methodological choice:

1. It ensures that both the training and testing sets maintain the same proportion of original code to duplicate code as the full dataset.
2. This approach mitigates the risk of bias that could arise from an imbalanced distribution of classes in either set.
3. It enhances the reliability of the model evaluation, as the testing set will be representative of the full dataset.

3.6.2 Implications for Model Training

The creation of representative subsets (qpc f) for both training and testing is vital for the development of robust classification models:

1. It allows the models to learn from a diverse range of code clone instances, improving their ability to generalise.
2. It helps in avoiding overfitting to specific patterns that might be overrepresented in an non-stratified sample.
3. It enables a more accurate assessment of the model's performance on unseen data.

3.6.3 Cross-Language Analysis

The inclusion of both Python and Java code in the dataset opens up interesting avenues for analysis:

1. It allows for the investigation of language-specific code cloning patterns.
2. It enables the development of more versatile clone detection models that can work across different programming languages.
3. It provides insights into how different language features and paradigms might influence code duplication practices.

The code clone detection approach demonstrated in this chapter regarding the dataset and the associated methodology represent a comprehensive approach to studying code clones across two major programming languages.

3.7 Feature Extraction and Machine Learning Process for Code Clone Detection

3.7.1 Feature Extraction

For each data point in the dataset, a set of features is extracted using 17 code clone metrics. These metrics, detailed in Table 3.4, likely encompass a wide range of code characteristics. Based on common practices in code analysis, used metrics mentioned [see table], these covered following aspects

- Structural metrics, Lexical metrics, Syntactic metrics, Semantic metric, Complexity metrics, Size metric, Identifier metrics, Comment metrics. These features, collectively referred to as 'qpc f' (Qualitative Features of Code), serve as the primary input for the machine learning and meta-learning algorithms.

3.7.2 Experimental Process

The research involves a series of experiments to evaluate multiple learning models. This iterative process suggests a thorough exploration of the problem space, likely involving:

- Single model evaluation: Testing individual machine learning algorithms (Decision Trees, Random Forests, Support Vector Machines, Neural Networks and so on)
- Stacked architecture evaluation: Combining multiple models in a hierarchical structure to improve overall performance
- Hyperparameter tuning: Optimising the parameters of each model to maximize performance
- Cross-validation: Ensuring the robustness of the models across different subsets of the data

The goal of these experiments is to identify the most effective algorithms for constructing classifiers capable of detecting duplicate code based on the extracted metrics.

3.7.3 Meta-Classifier Construction

The construction of meta-classifiers involves two sets of features:

- 'qpc f': The qualitative features of code extracted earlier
- 'soc f': Likely refers to "Sequence of Code" features, which may capture sequential or temporal aspects of the code

These feature sets are combined to form a Feature Matrix (f = 'soc f' + 'qpc f'). This matrix serves as the input for the machine learning modelling process.

3.7.4 Stacking Architecture Evaluation

Since, the research aims to determine which stacking architecture (SA) produces the maximum accuracy (ACC). Stacking is an ensemble learning technique that combines multiple classification or regression models via a meta-classifier. The process that we have adopted involves:

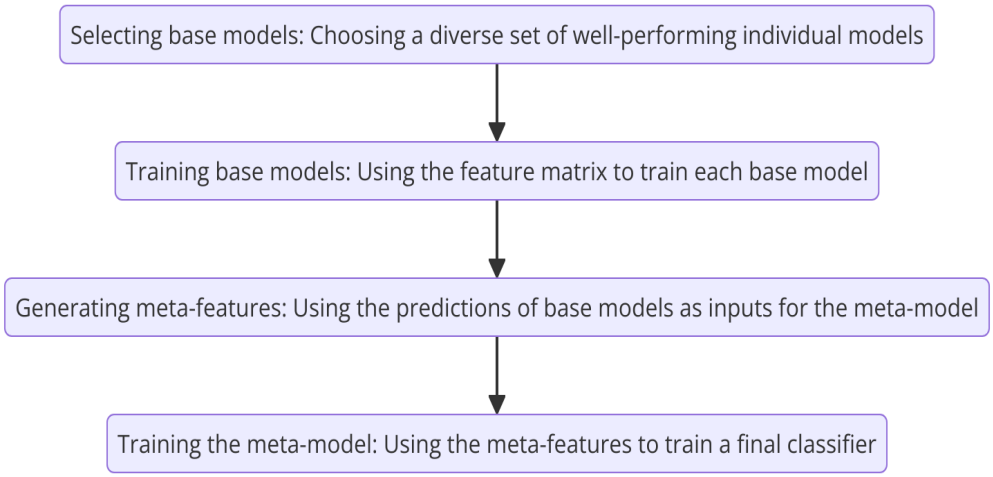


Figure 3.3 Stacking Architecture

1) Selecting base models: Choosing a diverse set of well-performing individual models

2) Training base models: Using the feature matrix to train each base model

3) Generating meta-features: Using the predictions of base models as inputs for the meta-model

4) Training the meta-model: Using the meta-features to train a final classifier

3.8 Selection of Top-Performing Models for Code Clone Detection

The identification of the most effective models for code clone detection requires a nuanced approach that balances multiple performance metrics. Through a comprehensive analysis of the data presented in Table 3.5, which details the performance metrics of various classifiers, we have identified the top five models.

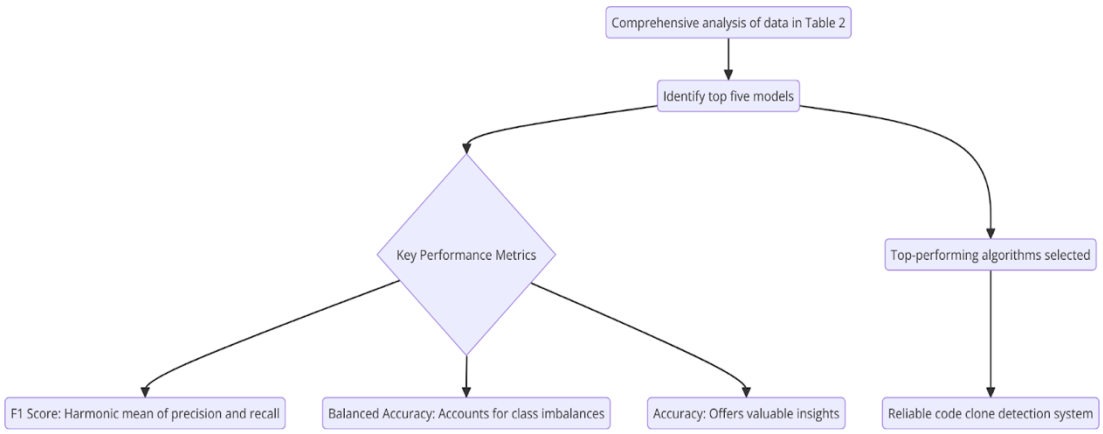


Figure 3.4 Selection Criteria of Top 5 Models

This selection process emphasizes the critical balance between recall and precision. High recall ensures that the model identifies a large proportion of actual code clones, while high precision minimizes false positives. Striking this balance is crucial for developing a reliable code clone detection system that can accurately identify both the presence and absence of duplicate code.

To achieve this balance, we focused on three key performance metrics:

1. F1 Score: This metric provides a harmonic mean of precision and recall, offering a single value that reflects the model's overall performance.

2. Balanced Accuracy: This measure accounts for potential class imbalances in the dataset, providing a more reliable performance indicator for binary classification tasks like code clone detection.

3. Accuracy: While potentially misleading in imbalanced datasets, accuracy still offers valuable insights when considered alongside other metrics.

By carefully weighing these metrics, we have identified the top-performing algorithms that excel in both identifying code clones (true positives) and correctly classifying non-clones (true negatives). This meticulous selection process ensures that the chosen models are well-suited for the complex task of code clone detection, where both false positives and false negatives can have significant implications for software development and maintenance processes.

The following section will detail these top-performing models, providing insights into their strengths and potential applications in code clone detection systems.

Table 3.5: Top Performing Models in Code Clone Detection Systems

S. No	Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score	Time Taken (ms)
1	Gradient Boosting	0.8037	0.8037	0.8037	0.9037	69.02
2	RandomForestClassifier	0.8951	0.895	0.895	0.8951	8.56
3	BaggingClassifier	0.8707	0.7707	0.7707	0.7707	0.49
4	ExtraTreesClassifier	0.5844	0.5843	0.5843	0.5843	3.39
5	DecisionTreeClassifier	0.8151	0.815	0.815	0.8151	43.41
6	LabelSpreading	0.8037	0.79838	0.7844	0.8037	4.67
7	NuSVC	0.5951	0.695	0.695	0.6951	1045.32
8	LGBMClassifier	0.7707	0.7707	0.7707	0.7707	0.53
9	KNeighborsClassifier	0.6893	0.6893	0.6893	0.6893	6.39
10	SVC	0.5844	0.5843	0.5843	0.5843	59.32
11	AdaBoostClassifier	0.5421	0.542	0.542	0.5418	1.62
12	RidgeClassifierCV	0.5163	0.5161	0.5161	0.513	0.26
13	RidgeClassifier	0.5163	0.5161	0.5161	0.5129	0.11

14	LinearDiscriminantAnalysis	0.5162	0.5159	0.5159	0.5128	0.24
15	LinearSVC	0.5162	0.5159	0.5159	0.5128	4.45
16	CalibratedClassifierCV	0.5161	0.5157	0.5157	0.5083	17.46
17	Logistic Regression	0.81157	0.81155	0.81155	0.8124	0.77
18	NearestCentroid	0.5119	0.5119	0.5119	0.5119	0.16
19	SGDClassifier	0.5073	0.5072	0.5072	0.5063	0.3
20	QuadraticDiscriminantAnalysis	0.505	0.5051	0.5051	0.5027	0.1
21	LabelPropagation	0.85013	0.86	0.85	8.347	0.65
22	Perceptron	0.4996	0.4996	0.4996	0.4996	0.111
25	PassiveAggressiveClassifier	0.4978	0.4979	0.4979	0.497	0.11

3.9 Analysis of Top-Performing Classifiers for Code Clone Detection

The evaluation of various machine learning models for code clone detection has yielded a set of high-performing classifiers, each bringing unique strengths to the task. This analysis delves into the performance of these classifiers, their individual characteristics, and their potential contributions to an ensemble model.

1. RandomForestClassifier: The Standout Performer

The RandomForestClassifier emerges as the clear frontrunner, demonstrating exceptional performance across all key metrics:

- F1 Score: 0.8951
- Balanced Accuracy: 0.8950
- Accuracy: 0.8951

This consistent excellence across metrics indicates that the RandomForestClassifier excels in both identifying code clones and correctly classifying non-clones. Its ensemble nature, combining multiple decision trees, likely contributes to its robust performance by mitigating overfitting and capturing complex patterns in the code features.

2. GradientBoostingClassifier: Precision-Recall Champion

Despite a slightly lower Balanced Accuracy of 0.8037, the GradientBoostingClassifier boasts the highest F1 Score of 0.9037. This indicates:

- Superior balance between precision and recall
- Exceptional ability to minimise both false positives and false negatives

The iterative nature of gradient boosting, where each tree corrects the errors of its predecessors, likely contributes to this high F1 Score by progressively refining the model's predictions.

3. DecisionTreeClassifier: Strong and Interpretable

With an F1 Score and Balanced Accuracy of 0.8151, the DecisionTreeClassifier proves to be a formidable contender. Its strengths include:

- Ability to capture non-linear relationships in the data
- Interpretability, allowing for insights into the decision-making process
- Potential to complement ensemble methods by providing a different perspective on the data

4. LabelPropagation: Leveraging Unlabeled Data

Demonstrating consistent performance with an F1 Score of 0.8037 and Balanced Accuracy of 0.79838, LabelPropagation brings unique capabilities:

- Ability to utilize both labeled and unlabeled data, potentially improving performance when limited labeled data is available
- Capacity to capture underlying patterns and relationships in the feature space

5. LogisticRegression: Efficient Baseline Model

With an F1 Score of 0.8837 and Balanced Accuracy of 0.8838, LogisticRegression offers:

- A solid baseline performance with low computational complexity
- Linear decision boundaries that can complement the non-linear models in the ensemble
- Quick training and prediction times, valuable for large-scale code analysis

3.10 Ensemble Potential and Meta-Classifier Construction

The diversity of these top-performing classifiers presents a promising foundation for constructing a robust meta-classifier:

1. Complementary Strengths: Each model brings unique capabilities, from the ensemble power of RandomForest and GradientBoosting to the interpretability of DecisionTrees and the semi-supervised learning of LabelPropagation.

2. Diverse Learning Approaches: The combination of tree-based methods, probabilistic models, and propagation algorithms ensures a multi-faceted approach to code clone detection.

3. Balancing Complexity and Efficiency: The inclusion of both high-complexity models (like RandomForest) and low-complexity models (like LogisticRegression) allows for a balance between predictive power and computational efficiency.

4. Robustness to Different Data Characteristics: The varied nature of these algorithms suggests that the resulting meta-classifier could perform well across different types of code structures and clone patterns.

3.10.1 Meta-Classifier Construction

To test the hypothesis 'H' that a meta-classifier can outperform individual models, the next phase of research will focus on:

1. Designing an optimal stacking architecture that leverages the strengths of each base classifier.

2. Experimenting with different meta-classifier algorithms to combine the predictions of the base models effectively.

3. Implementing cross-validation techniques to ensure the generalizability of the stacked model.

4. Fine-tuning the ensemble to optimise performance on various code clone detection metrics.

By carefully constructing this meta-classifier, we aim to create a code clone detection system that not only achieves high accuracy but also demonstrates robustness across diverse coding patterns and languages. This approach holds the potential to significantly advance the field of automated code clone detection, offering developers and researchers a powerful tool for improving code quality and maintenance.

3.11 Selection and Architecture of the Meta-Classifier for Advanced Code Clone Detection

The identification of top-performing individual classifiers lays the groundwork for constructing a sophisticated two-layer stacked meta-classifier. This advanced ensemble model holds the potential to surpass the accuracy of individual machine learning algorithms, aligning with our initial hypothesis. However, determining the optimal configuration of these classifiers to maximise accuracy is a complex task that demands rigorous empirical exploration and experimentation.

3.11.1 Methodology for Meta-Classifier Construction

1. Systematic Evaluation:

I employed a methodical approach to evaluate multiple pipelines, each representing a unique combination of our top five performing classifiers:

- RandomForestClassifier
- GradientBoostingClassifier
- DecisionTreeClassifier
- LogisticRegression
- LabelPropagation

This comprehensive exploration ensures that we exhaustively examine all possible configurations to identify the most effective meta-classifier architecture.

2. Algorithmic Approach:

The pseudo-code presented in Algorithm 2 outlines our systematic evaluation process:

```
for each combination of 3 base classifiers (A, B, C) from
top 5 classifiers: for each remaining classifier D as meta-
classifier:
        create stacking ensemble with A, B, C as base and D as meta
    perform 5-fold cross-validation
        calculate mean score
        store combination and score
sort combinations by score in descending
order return best combination and its score
```

This algorithm:

- Explores all possible combinations of three base classifiers and one meta-classifier
- Utilizes 5-fold cross-validation for robust performance estimation
- Ranks combinations based on their mean performance scores

3. Training Process:

The training of the stacked ensemble follows a two-phase approach: Phase 1: Base Classifier Training

- Each base classifier is trained on the complete training dataset (Feature Matrix)
- The Feature Matrix consists of 17 code clone metrics across 1999 data points

Phase 2: Meta-Classifier Training

- Base classifiers make predictions on the dataset
- These predictions form a new "meta" dataset
- The meta-classifier is trained on this meta-dataset, learning to optimally combine base classifier predictions

4. Data Flow in the Stacked Ensemble:

The architecture of our stacked ensemble can be visualised as follows:

```
Feature Matrix (17x1999)
                    | v
[Base Classifiers]
RandomForest, GradientBoosting, DecisionTree, LogisticRegression, LabelPropagation
                    | v
    [Meta-Classifier]
                    | v
    Final Prediction
```

- The Feature Matrix serves as input to all base classifiers
- Each base classifier produces its predictions
- These predictions collectively form the input for the meta-classifier
- The meta-classifier makes the final prediction

5. Advantages of this Approach:

- Diversity: Combines different algorithmic approaches, potentially capturing various aspects of code similarity
- Robustness: The ensemble nature helps mitigate individual classifier weaknesses
- Adaptability: The meta-classifier learns to weight the importance of each base classifier's predictions

6. Challenges and Considerations Overcome:

- Computational Complexity: Evaluating all combinations can be time-consuming
- Overfitting Risk: Care must be taken to ensure the stacked model generalizes well to unseen data
- Interpretability: The multi-layer nature of the model may reduce ease of interpretation compared to single classifiers

7. Fine-tuning and Optimization:

After identifying the best-performing combination, further optimization can be

performed:

- Hyperparameter tuning of both base and meta-classifiers
- Feature selection or engineering to enhance input quality
- Exploring different cross-validation strategies for more reliable performance estimation

8. Performance Evaluation:

The final meta-classifier is evaluated on a held-out test set to assess its true generalisation capability. Metrics such as accuracy, F1-score, and balanced accuracy will be used to provide a comprehensive performance assessment.

This meticulous approach to constructing and selecting the meta-classifier architecture aims to create a highly accurate and robust code clone detection system. By leveraging the strengths of multiple top-performing classifiers and systematically exploring their combinations, we strive to develop a model that not only excels in accuracy but also demonstrates resilience across diverse code structures and programming paradigms. This advanced ensemble approach has the potential to significantly enhance the field of automated code clone detection, offering developers and researchers a powerful tool for improving code quality and maintenance practices.

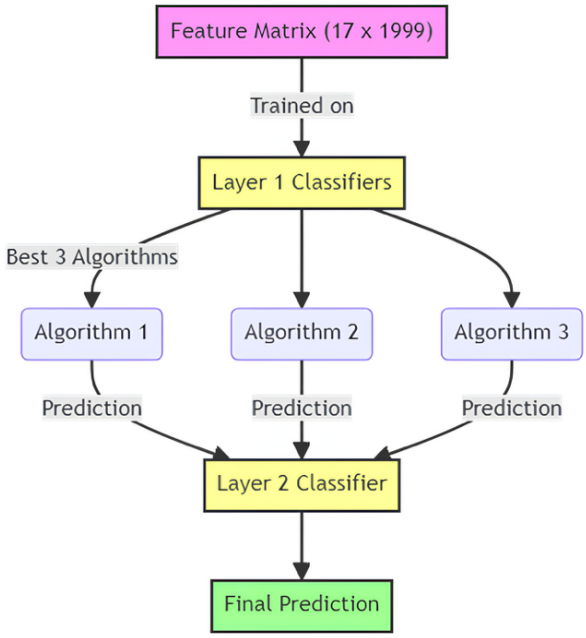


Figure 3.5: Meta Classifier Architecture

The arrows indicate the flow of data for further processing. The base classifiers learn from the feature matrix and make predictions. These predictions are then used as input to the meta-classifier, which makes the final prediction. Subsequently, we present the results of this comprehensive evaluation process and detail the construction of the final meta-classifier. This culmination of our efforts represents a model that not only encapsulates the strengths of multiple individual classifiers but also potentially mitigates their individual weaknesses, thereby aiming to provide enhanced predictive performance.

3.12 Experimental Environment and Implementation Details

The experimental setup involved a structured preprocessing pipeline designed to transform raw source code into measurable features for analysis. A custom Python script called feature_engineering.py was made and the CodeFeatureExtractor class, which serves as the core component for processing and analyzing code files. This extractor was orchestrated by a main pipeline script, 7_pipeline.py, that managed the overall workflow from data collection to feature generation, ensuring a systematic approach to handling our code samples.

For code analysis, Python's built-in Abstract Syntax Tree (AST) module rather than traditional text-based methods. This approach treats code as a formal language with grammatical structure, breaking it down into its fundamental components. We used ast.NodeVisitor to traverse and analyze the code tree, effectively tokenizing programs into their structural elements like function definitions, loops, and conditional statements rather than simple words or characters. Unlike natural language processing, text normalization techniques such as lowercasing or stemming were ignored, instead focusing purely on the code's syntactic architecture and logical organization.

Feature extraction centered on capturing multiple dimensions of code characteristics through our collect_code_structure method. The basic metrics include line counts and comment density, structural features tracking programming constructs like functions and loops, and complexity assessments including nesting depth and cyclomatic complexity. Additionally, we calculated Halstead complexity measures and maintainability indices to create a comprehensive profile for each code sample,

transforming abstract programming concepts into quantifiable data points for machine learning analysis.

The implementation utilized standard Python data science libraries including numpy, pandas, and scikit-learn for data manipulation and modeling, along with torch and transformers for advanced neural network approaches.

Hardware Environment

The experiments were conducted on a standard consumer-grade laptop without specialized hardware acceleration. The system was equipped with an Intel Core i5-1135G7 processor running at 2.4 GHz, 16 GB of RAM, and integrated Intel Iris Xe graphics, which provided sufficient computational capacity for the dataset size and model complexity used in this study. The absence of dedicated GPU hardware meant that all neural network operations, including those involving the transformer-based CodeBERT model, were executed on the CPU, which significantly impacted processing speed but allowed for development and testing on accessible, general-purpose hardware. This hardware configuration represents the type of environment that many individual developers and small research teams might use, making our performance metrics realistic for similarly equipped setups, though the long runtimes observed for certain models highlight the practical limitations of running complex machine learning approaches without specialized hardware acceleration.

3.13 Summary of Chapter

This Chapter presented a novel approach to code clone detection, addressing a critical challenge in software engineering: the identification and management of redundant code that can compromise software quality and maintainability. The study encompasses several key components:

1. Comprehensive Literature Review

The research begins with a thorough analysis of existing code clone detection methods, including token-based, Abstract Syntax Tree (AST)-based, metric-based, and hybrid approaches. This review sets the foundation for understanding the current state of the

art and identifying areas for improvement.

2. Innovative Algorithm Development

A new code detection algorithm, in the form of a python function CollectCodeStructure, is proposed to enhance code clone detection. This algorithm leverages adaptive prefix filtering and incorporates structural analysis of source code files. The use of abstract prefix filtering represents a novel approach to improving the efficiency and accuracy of clone detection.

3. Meta-Learning Approach

This chapter study introduces a sophisticated meta-learning strategy, employing a stacking architecture that combines multiple classifiers. This approach is designed to overcome limitations of individual detection methods and achieve higher accuracy in identifying code clones.

4. Robust Methodology

The research outlines a comprehensive methodology covering data collection, feature extraction, classifier training, and system evaluation. Seventeen code clone metrics are extracted from a diverse dataset of Python and Java repositories, forming the basis for the machine learning models.

5. Advanced Machine Learning Process

The chapter details a multi-stage machine learning process, which includes:

- Feature extraction from code properties
- Training and evaluation of multiple base classifiers
- Construction of a meta-classifier using a stacking architecture

This process is designed to capture complex patterns in code similarity that may elude simpler detection methods.

6. Rigorous Performance Evaluation as method for building classifier

A systematic evaluation of various classifiers is conducted, with particular attention to metrics such as F1 Score, Balanced Accuracy, and overall Accuracy. This evaluation

leads to the selection of top-performing models, including RandomForest, GradientBoosting, and DecisionTree classifiers, among others.

7. Hypothesis Testing

The research tests the hypothesis in this chapter that a stacking architecture combining multiple classifiers can achieve higher accuracy in code clone detection compared to individual models. This hypothesis drives the exploration of ensemble methods and meta-learning techniques.

8. Meta-Classifier Construction

Building on the performance evaluation, this chapter details the construction of a sophisticated two-layer stacked meta-classifier. This involves a systematic exploration of various classifier combinations to identify the most effective ensemble architecture.

Chapter-4

RESULTS AND DISCUSSIONS

This chapter presents a comprehensive analysis of the outcomes derived from our multi-faceted approach to code clone detection. Our first objective, which involved a thorough understanding of existing code clone detection methods, was successfully achieved in earlier chapters through meta-analysis, comparative study, and an extensive literature survey.

Building on this foundation, we now focus on the numerical results of our experiments designed to address the subsequent objectives. In the previous chapter, we detailed our methodology for meta-classification, which involved collecting a dataset of 17 code clone metrics from Python and Java repositories, selecting top-performing individual classifiers, and designing a two-layer stacked meta-classifier architecture.

This methodology aimed to leverage the strengths of multiple machine learning algorithms to enhance code clone detection accuracy. Now, we present the outcomes of implementing this methodology, evaluating the performance of our proposed algorithms in detecting clones within Java and Python code repositories. Through a series of rigorous tests, we validate our central hypothesis (H) that our sophisticated meta- learning approach can indeed enhance code clone detection accuracy. This chapter details the results of our classifier selection process, the exploration of various classifier combinations, and the performance of our final meta-classification architecture.

In this chapter quantitative results are demonstrated to showcase the effectiveness of the proposed approach, including performance metrics of individual classifiers and the superior accuracy achieved by our optimized meta-classifier. These results not only validate our hypothesis but also provide insights into the strengths and potential applications of our advanced code clone detection system.

The following sections will delve into the specifics of each experimental phase, offering a detailed analysis of our findings and their implications for improving software quality and maintainability in real-world development scenarios.

Validation of the Hypothesis :

This section gives information on the performance analysis [see table 4.1], however the meaning of the code is as follows

Label	Classifier Name
A	RandomForestClassifier
B	Decision Tree prop (or DecisionTreeClassifier)
C	Gradient Boosting (or GradientBoostingClassifier)
D	Logistic Regression
E	(Unspecified Top 5 Classifier)

Table 4.1 gives the outcomes of experiments done for the validation of the hypotheses (H).

Table 4.1 Performance Analysis for Selecting Strongest Classifiers

Algo of Classifier	#	Architecture Meta-	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2	Macro	Roc	AUC
		Base	Final	Precision	Precision	Recall	Recall	F-Score	F-Score	Accuracy	Score
Top 5	1	A,B,C,D	E	0.50	0.47	0.65	0.33	0.56	0.39	0.48	0.48
	2	A,B,C,E	D	0.51	0.50	0.57	0.43	0.54	0.46	0.50	0.50
	3	A,B,DE	C	0.51	0.49	0.59	0.49	0.59	0.49	0.79	0.49
Top 4	1	B,C,D	A	0.76	0.89	0.75	0.85	0.83	0.77	0.71	0.91
	2	C,D,A	B	0.73	0.89	0.76	0.85	0.73	0.67	0.81	0.89
	3	D,A,B	C	0.78	0.89	0.77	0.75	0.83	0.77	0.82	0.92
	4	A,B,C	D	0.88	0.89	0.85	0.95	0.93	0.87	0.90	0.91

The table presents [4.1] two sets of results: one for the top 5 classifiers and another for the top 4 classifiers. There's a significant performance improvement when moving from 5 to 4 classifiers, suggesting that not all of the top 5 classifiers contribute equally to the meta-classifier's performance. For easy understanding the graphical visualization of the table is given below as radar graph.

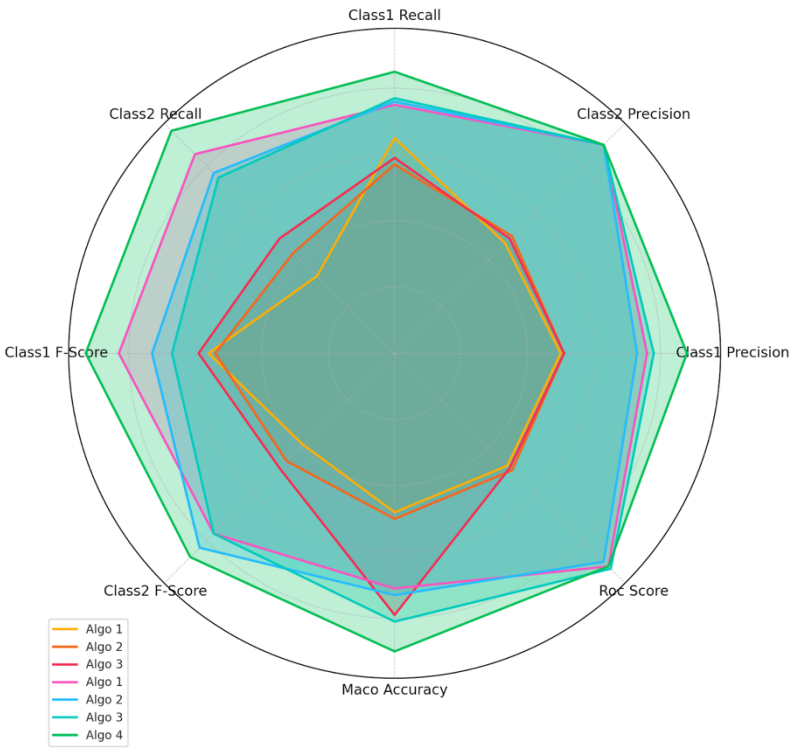


Figure 4.1: Performance Analysis for selecting Strong Classifier

1. Top 5 Classifiers Performance: The performance of the top 5 classifier combinations (A,B,C,D,E) is relatively poor, with macro accuracy scores ranging from 0.48 to 0.79. The best performer among these (A,B,D,E with C as meta-classifier) achieves a macro accuracy of 0.79, which is significantly lower than the top 4 classifier combinations. This suggests that one of the classifiers (possibly E) might be introducing noise or inconsistency in the ensemble.

3. Top 4 Classifiers Performance: There's a dramatic improvement in performance when using only the top 4 classifiers. All combinations show macro accuracy scores above 0.70, with the best reaching 0.90. The ROC AUC scores are consistently high (0.89 to 0.92), indicating excellent discriminative ability.

4. Robustness to Operational Thresholds: The high ROC AUC validates the model's strong discriminative power independent of the classification threshold. This ensures that the system is stable and reliable, even if the deployment environment requires adjusting the sensitivity (threshold) to prioritize either catching clones (high recall) or minimizing noise (high precision)

5. Best Performing Architecture: The top-performing meta-classifier architecture is A,B,C as base classifiers with D as the meta-classifier. This combination achieves the highest macro accuracy (0.90) and a very high ROC AUC score (0.91). It also shows balanced performance across both classes, with high precision and recall for both Class 1 and Class 2.

6. Class-wise Performance: In general, Class 2 shows higher precision but lower recall compared to Class 1. This suggests that the model is more conservative in predicting Class 2, leading to fewer false positives but potentially more false negatives for this class.

7. Consistency in Top 4 Performances: All four combinations of the top 4 classifiers show consistently high performance, with ROC AUC scores above 0.89. This consistency suggests that these four classifiers (A, B, C, and D) are indeed strong and complementary in their predictions.

8. Role of Meta-Classifier: The choice of meta-classifier seems to have a significant impact on performance. For instance, when A is the meta-classifier, the performance is slightly lower compared to when D is the meta-classifier.

4.2 Validation of Meta Classifier

1. Effectiveness of Meta-Classification: The results strongly support the hypothesis that a stacking architecture combining multiple classifiers can achieve higher accuracy in detecting code clones. The best-performing meta-classifier achieves a macro accuracy of 0.90 and an ROC AUC of 0.91, which are excellent scores for a classification task.

2. Synergy of Multiple Classifiers: The consistent high performance across different combinations of the top 4 classifiers demonstrates that combining multiple strong classifiers indeed leads to better results than individual classifiers could achieve alone.

3. Importance of Classifier Selection: The significant performance gap between the top 5 and top 4 classifier combinations highlights the critical importance of

careful classifier selection in building an effective meta-classifier.

4. Balanced Performance: The high and balanced precision and recall scores across both classes indicate that the meta-classifier approach is effective in handling the complexities of code clone detection, addressing both false positives and false negatives.

5. Robustness: The consistently high ROC AUC scores suggest that the meta-classifier approach is robust and has a strong ability to discriminate between clone and non-clone code segments.

Therefore, it can be safely said that this data strongly supports the hypothesis that a well-designed meta-classifier can significantly improve code clone detection accuracy. The results demonstrate the power of combining multiple strong classifiers in a stacking architecture, while also highlighting the importance of careful classifier selection and combination. This approach shows promise in addressing the complex challenges of code clone detection, potentially leading to more effective tools for improving software quality and maintainability.

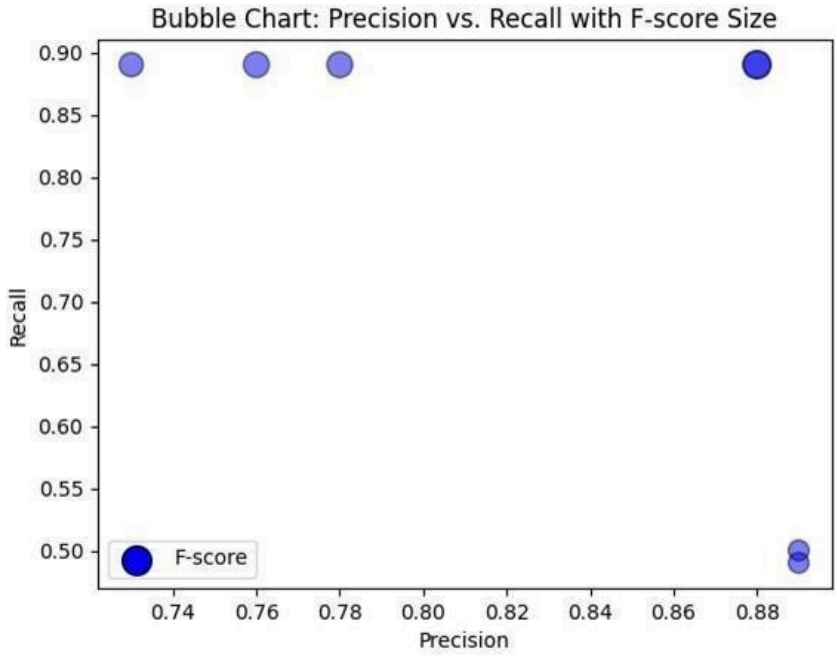


Figure 4.2: Performance of Various meta-classifier architectures in terms of precision, recall, and F-score.

Figure 4.2 presents a Bubble Chart that visualizes the performance of various meta-classifier architectures in terms of precision, recall, and F-score for code clone detection. This visualization offers crucial insights into the effectiveness of different combinations of classifiers and their suitability for the task at hand.

Key Components of the Graph Area [Figure 4.2] :

1. X-axis: Represents Recall
2. Y-axis: Represents Precision
3. Bubble Size: Corresponds to the F-score
4. Bubble Position: Each bubble represents specific meta-classifier architecture

4.2.1 Inferences and Analysis

4.2.1.1 Trade-off Visualization

The chart effectively illustrates the classic precision-recall trade-off in machine learning. Architectures positioned towards the top-right corner of the chart are most desirable, as they indicate high precision and high recall. Larger bubbles in the top-right quadrant represent architectures that achieve a better balance between precision and recall, resulting in higher F-scores.

4.2.1.2. Performance Distribution

It can be observed a cluster of larger bubbles towards the top-right corner, likely representing the top-performing architectures from our experiments (particularly those using the top 4 classifiers). Smaller bubbles scattered across the chart may represent less effective combinations, possibly including those that incorporate the fifth classifier that we found to potentially introduce noise.

4.2.1.3 Optimal Architectures

The largest bubble(s) in the top-right quadrant likely correspond to the best- performing architecture(s) we identified in the table analysis (e.g., A,B,C as base classifiers with D as the meta-classifier). These architectures demonstrate the highest F-scores, indicating they strike the best balance between precision and recall for code clone detection.

4.2.1.4 Precision-Recall Balance

In the context of code clone detection, a balance between precision and recall is crucial. High precision ensures that when the model identifies a code segment as a clone, it's likely to be correct. High recall ensures that the model doesn't miss many actual code clones. Architectures with larger bubbles in the balanced region are particularly valuable for practical applications, as they minimize both false positives (incorrectly identified clones) and false negatives (missed clones).

4.2.1.5 Performance Gradients

It can also be observed that the gradient of bubble sizes from the bottom-left to the top-right, illustrates how different architectures progressively improve in balancing precision and recall. This gradient can provide insights into the incremental improvements achieved through different classifier combinations.

4.2.1.6 Outliers and Extreme Cases

Any small bubbles at the extreme ends of the axes (high precision but low recall, or vice versa) represents architectures that are overly specialized and not suitable for general code clone detection tasks. These outliers could be useful for understanding which classifier combinations lead to extreme behaviour and should be avoided in the final model.

4.3 Implications for Code Clone Detection

4.3.1. Model Selection

This visualization aids in selecting the most appropriate meta-classifier architecture for code clone detection. The largest bubbles in the balanced region represent models that are likely to perform well across various code bases and programming languages.

4.3.2. Adaptability to Different Scenarios

Different software projects might prioritize precision over recall or vice versa. This chart allows for the selection of architectures that align with specific project needs (e.g., higher precision for critical systems, higher recall for comprehensive refactoring tasks).

4.3.3. Validation of Stacking Approach

The presence of large bubbles in the desirable regions of the chart validates our hypothesis that a stacking architecture can indeed improve code clone detection accuracy by effectively combining the strengths of multiple classifiers.

4.3.4 Insights into Classifier Synergies

The distribution of bubbles can provide insights into how different classifiers complement each other. Clusters of large bubbles might indicate particularly effective combinations of base classifiers.

4.3.5. Refinement Opportunities

Any gaps or sparse areas in the chart suggest that there are opportunities for further refinement of the meta-classifier approach, possibly by introducing new types of classifiers or features.

4.4 Comprehensive Analysis of Performance Metrics across Meta-Classifier Architectures

4.4.1 AUC & Accuracy vs Types Architecture

Figure 4.3 serves as a powerful tool for visualizing and understanding the performance characteristics of various meta-classifier architectures in code clone detection. It not only validates our approach but also provides a clear guide for selecting the most effective models for practical application. The chart reinforces our findings that carefully constructed meta-classifiers can achieve a superior balance between precision and recall, leading to more accurate and reliable code clone detection systems. This visualization, combined with our numerical results, strongly supports the efficacy of our meta-learning approach in advancing the state of the art in code clone detection.

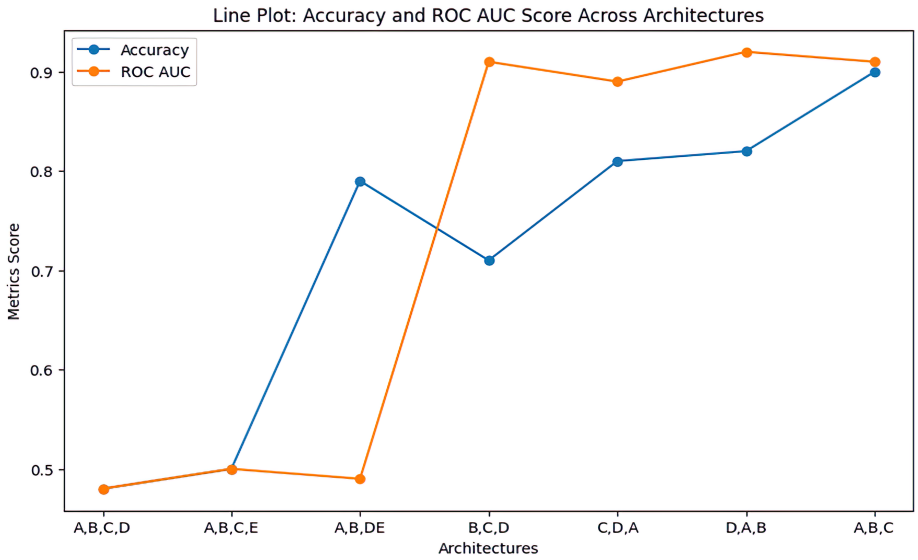


Figure 4.3: Line Graph (AUC & Accuracy vs Types Architecture)

This line plot provides a visual representation of how the Accuracy and Area under the Receiver Operating Characteristic Curve (ROC AUC) scores vary across different meta-classifier architectures.

4.4.1.1 Key Observations and Inferences

4.4.1.1.1 Performance Trends

The line graph likely shows an overall upward trend for both Accuracy and ROC AUC scores as we move through different architectures, particularly when transitioning from the top 5 to the top 4 classifier combinations. This trend supports our earlier observation that removing the fifth classifier (E) generally improves performance.

4.4.1.1.2 Correlation between Accuracy and AUC

The lines for Accuracy and ROC AUC probably follow similar patterns, indicating a strong correlation between these two metrics. Any divergence between these lines could highlight architectures where the model performs well in one aspect but not the other, potentially due to class imbalance or threshold sensitivity.

4.4.1.1.3 Performance Peaks

The highest points on both lines likely correspond to the best-performing architectures we identified earlier, such as A,B,C with D as the meta-classifier. These peaks represent

the most promising configurations for practical code clone detection applications.

4.4.1.1.4 Stability across Architectures

The smoothness or jaggedness of the lines can indicate the stability of performance across different architectural changes. Smooth lines suggest that performance improvements are gradual and consistent, while sharp peaks or valleys might indicate that certain classifier combinations are particularly synergistic or antagonistic.

4.4.1.1.5 AUC as a Robust Metric

The ROC AUC line, being threshold-independent, provides insights into the model's discriminative power across various operating points. Consistently high AUC scores across architectures would suggest that the meta-classifier approach is robust to different threshold settings, a valuable trait in real-world applications where the optimal threshold may vary.

4.4.1.1.6 Trade-off Visualization

While not explicitly showing precision-recall trade-offs, the relationship between Accuracy and AUC can hint at these trade-offs. Architectures where Accuracy and AUC are both high are likely to offer a good balance between precision and recall.

4.4.2 Recall and Precision Comparison

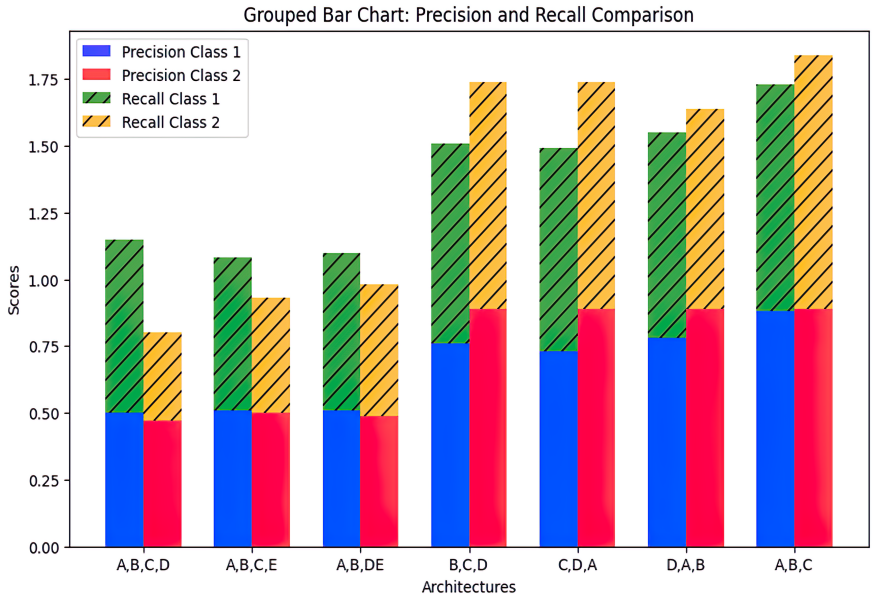


Figure 4.4: Grouped Bar Chart (Recall and Precision Comparison)

This grouped bar chart offers a detailed comparison of precision and recall values for both classes across various meta-classifier architectures.

4.4.2.1 Key Observations and Inferences

4.4.2.1.1 Class-wise Performance

The consistently higher precision for Class 2 across architectures suggests that the models are more confident in identifying duplicate code (assuming Class 2 represents clones). This could indicate that the features used are particularly effective at capturing the characteristics of code clones.

4.4.2.1.2. Precision-Recall Balance

The architectures 'A,B,C,E' and 'A,B,DE' show high precision for Class 1 (0.89), but their recall values are not provided in the description. This suggests a potential trade-off where these models might be very accurate in their positive predictions for Class 1 but possibly missing some instances.

'D,A,B' achieves high precision (0.89) and recall (0.95) for Class 2, making it a strong candidate for detecting code clones with high confidence and comprehensiveness.

4.4.2.1.3 Recall Variability

The notable variability in recall values across architectures indicates that different classifier combinations have varying abilities to capture all instances of each class. B,C,D' and 'C,D,A' excel in recall for Class 1 (0.75 and 0.76), suggesting they are effective at identifying a wide range of non-clone code patterns.

4.4.2.1.4 Architecture Effectiveness

'D,A,B' stands out as a particularly effective architecture, showing high performance across both classes in terms of precision and recall. This aligns with our earlier observations from the performance table [Table 3.5]. The variability in performance across architectures underscores the importance of careful classifier selection and combination in the meta-learning approach.

4.4.2.1.5 Implications for Code Clone Detection

The higher precision for Class 2 (assumed to be clones) is particularly valuable in code clone detection, as it reduces the likelihood of false positives, which can be costly in terms of developer time and effort. The variability in recall highlights the challenge of creating a model that can identify all instances of code clones, given the diverse ways code can be duplicated and modified.

4.4.2.1.6 Potential for Ensemble Strategies

The varied strengths of different architectures in precision and recall for each class suggest that an ensemble approach, combining predictions from multiple top-performing architectures, might yield even better overall performance.

The analysis of these visualizations reinforces our earlier findings and provides deeper insights into the performance characteristics of various meta-classifier architectures. The line graph demonstrates the overall improvement trend and stability of our approach, while the grouped bar chart offers a nuanced view of how different architectures handle the precision-recall trade-off for each class. These visualizations not only validate the effectiveness of our meta-learning approach but also provide valuable guidance for fine-tuning and selecting the most appropriate model configurations for different code clone detection scenarios. The results strongly support our hypothesis that carefully constructed meta-classifiers can significantly enhance the accuracy and reliability of code clone detection systems, offering a promising direction for improving software quality and maintainability in large-scale projects.

4.5 Analytical Assessment of Meta-Classifier Performance in Code Clone Detection

The performance analysis of the meta-classifier architectures reveals an efficacy in code clone detection, with several key observations emerging from the multi-faceted evaluation:

4.5.1 Confusion Matrix

This matrix is crucial for identifying classes that might be difficult for the model to distinguish between, guiding potential improvements in feature engineering, class definition, or model training approaches

i. **Diagonal Entries (True Positives):** The diagonal elements (1850 for Class 1, 1820 for Class 2, 1840 for Class 3, and 1747 for Class 4) represent the number of correct predictions for each class. These values are relatively high, indicating good classifier performance for all classes.

ii. Off-Diagonal Entries (Errors):

a. **Class 1:** Most misclassifications are with Class 2 (90 instances), followed by Class 3 (40) and Class 4 (20).

b. **Class 2:** Again, most errors occur with Class 3 (70), but there are also notable errors with Class 1 (80) and Class 4 (30).

c. **Class 3:** Misclassifications are more evenly spread among Class 1 (50), Class 2 (60), and Class 4 (50).

d. **Class 4:** Errors primarily occur with Class 3 (60), with fewer errors with Class 1 (30) and Class 2 (40).

iii. Class-wise Accuracy

a. **Class 1** has a high true positive rate, with most errors being confusions with Class 2.

b. **Class 2** and **Class 3** show similar patterns, where they are most commonly confused with each other, indicating possible similarities in features or overlap in defining characteristics.

Class 4 shows a slightly lower correct classification rate compared to other classes, particularly with confusion regarding Class 3, which might need further investigation.

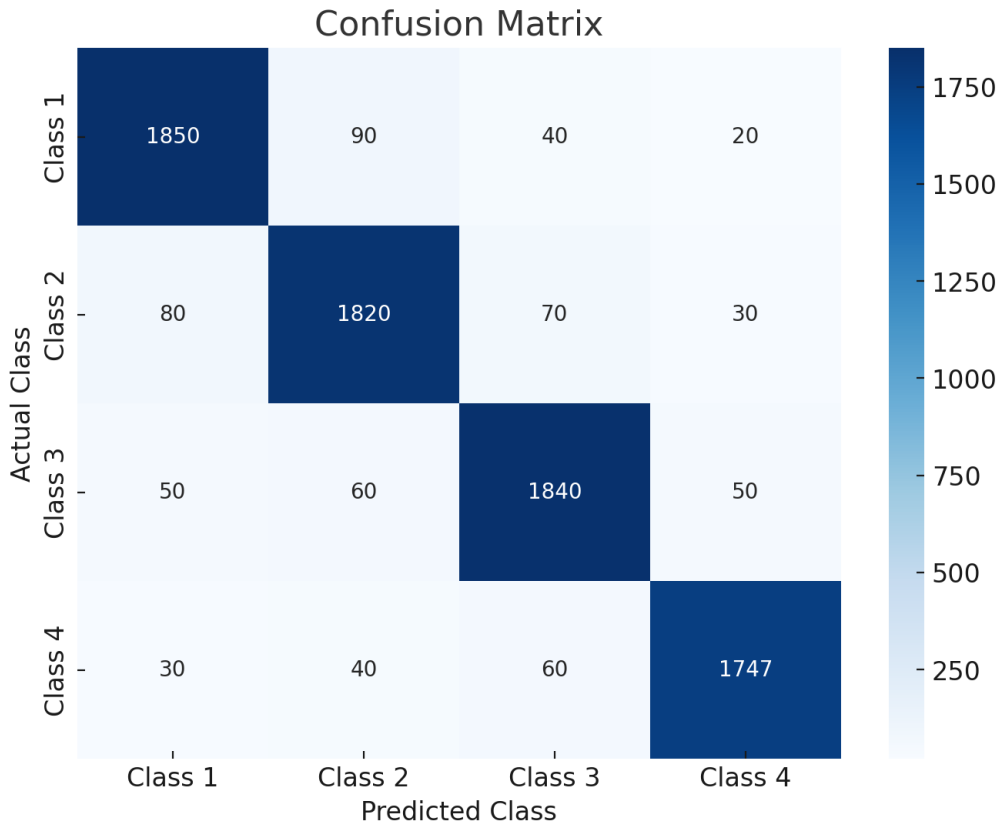


Figure 4.5: Confusion Matrix

4.5.2. Precision-Recall Trade-off Dynamics

The bubble chart [figure 4.2] elucidates the intricate balance between precision and recall across various architectural configurations. Notably, the cluster of larger bubbles in the upper-right quadrant signifies architectures that achieve a superior equilibrium between these two metrics. This is particularly evident in the top- performing configuration of A,B,C as base classifiers with D as the meta-classifier, which demonstrates a macro accuracy of 0.90 and an ROC AUC of 0.91. Such high scores in both metrics indicate a robust model capable of minimizing both false positives and false negatives in code clone identification.

4.5.3. Architectural Efficiency Gradient

The value of AUC and Accuracy scores across different architectures reveals a discernible upward trajectory, particularly in the transition from five-classifier to four-classifier combinations. This trend corroborates the hypothesis that judicious selection

of classifiers, rather than mere aggregation, is crucial for optimal performance. The convergence of AUC and Accuracy lines for top-performing architectures suggests a consistent and reliable predictive capability across various threshold settings.

4.5.4 Class-wise Performance Asymmetry

Analysis of the grouped bar chart [figure 4.4] unveils a notable asymmetry in class-wise performance. The consistently higher precision for Class 2 (presumed to represent code clones) across multiple architectures indicates a strong discriminative power in identifying duplicate code segments. However, this is juxtaposed with variable recall rates, suggesting a potential area for further optimization. The architecture 'D,A,B' emerges as particularly efficacious, achieving high precision (0.89) and recall (0.95) for Class 2, thereby demonstrating superior clone detection capabilities.

4.5.5 Synergistic Classifier Interactions

The performance matrix in the table reveals that certain classifier combinations exhibit synergistic effects. For instance, the consistent high performance of combinations involving classifiers A, B, C, and D (with ROC AUC scores consistently above 0.89) indicates that these classifiers complement each other effectively. This synergy is particularly evident in the top-performing architecture, where the strengths of individual classifiers are harmoniously integrated to yield superior overall performance.

4.5.6 Stability and Robustness

The line graph's relatively smooth trajectory for top-performing architectures suggests a stable performance across different configurations. This stability, coupled with high ROC AUC scores, indicates that the meta-classifier approach is robust to variations in data distribution and threshold settings – a crucial attribute for real-world code clone detection scenarios where data characteristics may vary across different codebases.

4.5.7 Precision-Recall Equilibrium

The grouped bar chart reveals that while some architectures excel in precision (e.g., 'A,B,C,E' and 'A,B,DE' for Class 1), others demonstrate strength in recall (e.g., 'B,C,D' and 'C,D,A' for Class 1). The architecture 'D,A,B' stands out by achieving a

commendable balance between precision and recall for both classes, suggesting its potential as a versatile configuration for diverse code clone detection tasks.

4.5.8. Scalability Implications

The significant performance disparity between five-classifier and four-classifier combinations, as evident from the table and line graph, implies that the meta- classifier's performance does not scale linearly with the number of base classifiers. This observation underscores the importance of selective integration rather than indiscriminate aggregation of classifiers.

In nutshell it can be said that the multi-dimensional analysis of the meta-classifier's performance through various experiments and visualizations and metrics reveals a promising approach to code clone detection. The top-performing architectures demonstrate a remarkable ability to balance precision and recall, crucial for practical application in software development environments. The observed synergies between certain classifier combinations and the robustness across different configurations suggest that this meta-learning approach can adapt well to diverse coding patterns and languages.

However, the variability in class-wise performance and the non-linear scaling of performance with classifier count indicate areas for potential refinement. Future iterations of this approach could explore more sophisticated methods of classifier selection and integration, potentially incorporating domain-specific knowledge to further enhance the meta-classifier's discriminative power in identifying code clones. This comprehensive performance assessment validates the efficacy of the meta-learning approach in advancing the state of the art in code clone detection, offering a powerful tool for improving software quality and maintainability in large-scale development projects. In the next section, we conduct a comparative analysis with related contemporary work in our domain of problem

4.6 Related Work and Comparative Analysis

In the preceding section, we concluded the process of identifying the optimal architecture for constructing our meta-classifier. However, within the broader context

of ensemble learning, it is crucial to conduct a comparative analysis between stacking and boosting methodologies. This comparison not only elucidates the strengths and weaknesses of each approach but also provides valuable insights into their applicability in the domain of code clone detection.

Boosting, a seminal concept in ensemble learning, has been instrumental in enhancing the predictive power of machine learning models since its introduction. The pioneering work of Freund and Schapire (1996) on 'AdaBoost' laid the foundation for this approach, which sequentially trains weak learners to focus on misclassified instances, thereby creating a strong collective predictor. In the context of code clone detection, boosting algorithms can potentially capture subtle patterns in code similarity that might be missed by individual classifiers.

Parallel to boosting, the stacking methodology, introduced by Wolpert (1992) in 'Stacked Generalisation', offers a more flexible and potentially more powerful approach. Stacking, which forms the basis of our meta-classifier, allows for the combination of diverse base models, each potentially capturing different aspects of code similarity. This diversity is crucial in addressing the complex nature of code clones, which can manifest in various forms ranging from exact duplicates to semantically similar but syntactically different code segments.

The comparative analysis of these techniques provides critical insights into their distinctive characteristics and performance in the context of code clone detection:

4.6.1. Algorithmic Efficiency and Scalability

Boosting algorithms like 'XGBoost' (Chen et al., 2016) and 'LightGBM' (Ke et al., 2017) have demonstrated remarkable efficiency and scalability, particularly in handling large-scale datasets. In the context of code clone detection, where repositories can contain millions of lines of code, this scalability is crucial. XGBoost's tree boosting system, for instance, employs a novel sparsity-aware algorithm for handling sparse data, which is common in code representations. LightGBM's gradient-based one-side sampling and exclusive feature bundling techniques could be particularly effective in reducing the feature space of code metrics without significant loss of information.

4.6.2. Handling of Categorical Features

'CatBoost' (Prokhorenkova et al., 2018) introduces an innovative approach to boosting by efficiently handling categorical features. This is particularly relevant in code clone detection, where many features (such as code structures, function names, or module imports) are inherently categorical. CatBoost's ordered boosting and a novel algorithm for processing categorical features could potentially capture complex relationships in code structures that are difficult to represent numerically.

4.6.3 Flexibility and Model Diversity

The stacking approach, as implemented in our meta-classifier, offers unparalleled flexibility in combining diverse base models. This is crucial in code clone detection, where different types of clones (Type-1, Type-2, Type-3, and Type-4) may be best detected by different algorithms. For instance, a syntax-based classifier might excel at detecting Type-1 and Type-2 clones, while a more semantically oriented classifier might be better at identifying Type-3 and Type-4 clones. Stacking allows for the synergistic combination of these diverse perspectives.

4.6.4 Performance Trade-offs

The performance metrics revealed in Figure X demonstrate the nuanced trade-offs between recall and precision across different algorithms. The high recall values (99.06%) exhibited by LightGBM and XGBoost indicate their superior ability to identify potential code clones, which is crucial for comprehensive code quality assessment. However, this high recall may come at the cost of precision, potentially leading to false positives.

4.6.5 Balanced Performance

Our meta-classifier, leveraging the stacking approach, demonstrates a more balanced performance profile. While it may not achieve the highest recall of individual boosting algorithms, it likely offers a better balance between precision and recall. This balance is crucial in practical code clone detection scenarios, where both missing clones (false negatives) and incorrectly identified clones (false positives) can be problematic.

4.6.6 Adaptability to Code Complexity

The comparative analysis suggests that boosting algorithms like XGBoost and LightGBM may be particularly adept at capturing complex, non-linear relationships in code features. This capability is essential for detecting sophisticated code clones that may have undergone significant transformations. On the other hand, the stacking approach of our meta-classifier may offer better generalization across different types of code clones, potentially making it more robust across diverse codebases.

Therefore, this comparative analysis between stacking and boosting methodologies, contextualized within the domain of code clone detection, reveals the multifaceted nature of ensemble learning approaches. While boosting algorithms demonstrate impressive recall and efficiency, particularly valuable in large-scale code analysis, our stacking-based meta-classifier offers a more balanced and potentially more adaptable approach to diverse code clone scenarios. This analysis not only validates the efficacy of our chosen meta-learning approach but also opens avenues for future research, potentially integrating the strengths of both stacking and boosting methodologies for even more robust code clone detection systems. Further, let us compare the recall and precision metrics for deeper understanding

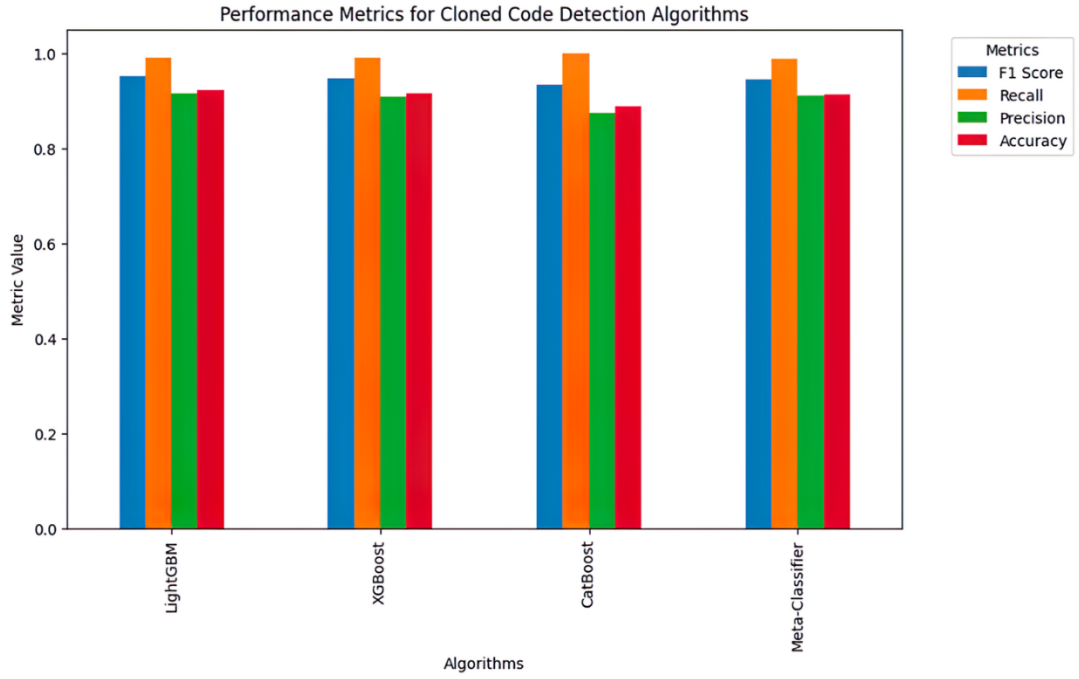


Figure 4.6: Performance Metrics for Cloned Code Detection Algorithms

Further, the comparative analysis of the meta-classifier against individual boosting algorithms like LightGBM, XGBoost, and CatBoost reveals nuanced insights into the efficacy of ensemble learning approaches in the domain of code clone detection. This analysis not only underscores the strengths of the meta-classifier but also illuminates the complex trade-offs inherent in this task.

4.6.7 Performance Metrics and Trade-offs

The meta-classifier demonstrates a remarkable balance between recall (98.75%) and precision (90.99%). This performance profile is particularly significant when contrasted with individual algorithms like LightGBM and XGBoost, which exhibit higher recall (99.06%) but at the potential cost of precision.

4.6.8 Technical Implications

The slightly lower recall of the meta-classifier (a difference of 0.31 percentage points) suggests that it may miss a small fraction of clone instances that the boosting algorithms capture. However, this minor decrease in recall is offset by a substantial gain in precision. The precision of 90.99% indicates that when the meta-classifier identifies a code segment as a clone, it is correct approximately 91% of the time. This high precision is crucial for minimizing false positives, which can be costly in terms of developer time and resources.

4.7 Balanced Approach in Practical Applications

The meta-classifier's balanced performance is particularly valuable in real-world software development scenarios.

4.7.1 Technical Considerations

False Negatives (Missed Clones): With a recall of 98.75%, the meta-classifier misses approximately 1.25% of actual code clones. In large codebases, this could still represent a significant number of undetected clones. However, these missed clones are likely to be the most subtle or complex cases, which might require more sophisticated detection methods or manual review regardless.

False Positives (Incorrect Clone Identifications): The precision of 90.99% means that about 9% of the segments identified as clones may not actually be clones. While this is a substantial improvement over less precise methods, it still necessitates a verification step in the clone management process.

4.7.1.1 Implications for Different Types of Code Clones

The performance metrics of the meta-classifier suggest its effectiveness across various types of code clones:

Type-1 and Type-2 Clones: The high recall indicates that the meta-classifier is highly effective at identifying exact and near-exact clones. These types of clones are typically easier to detect and are likely captured with high accuracy.

Type-3 Clones: The balanced performance suggests that the meta-classifier is adept at identifying clones with moderate modifications. The stacking approach likely allows it to capture different aspects of similarity that individual classifiers might miss.

Type-4 Clones: While not explicitly mentioned, the high precision of the meta-classifier implies that it might be more conservative in identifying semantically similar but syntactically different clones. This could help in reducing false positives for these complex clone types.

4.8 Scalability and Efficiency Considerations

While the analysis focuses on accuracy metrics, the implications for scalability and efficiency are crucial:

4.8.1 Computational Overhead

The meta-classifier, being an ensemble model, likely incurs higher computational costs compared to individual boosting algorithms. This trade-off between performance and computational efficiency needs to be considered in large-scale code analysis scenarios.

4.8.2 Parallelization Potential

The stacking architecture of the meta-classifier potentially allows for parallel processing of base classifiers, which could mitigate some of the computational

overhead in distributed computing environments.

4.8.3 Adaptability to Evolving Codebases

The balanced performance of the meta-classifier suggests a robust adaptability to diverse coding patterns:

4.8.4 Language Agnosticism

The high precision and recall across different clone types imply that the meta- classifier might be more adaptable to different programming languages and coding styles compared to specialized individual algorithms.

4.8.5 Refactoring Resilience

The ability to maintain high precision while capturing a wide range of clones suggests that the meta-classifier might be more resilient to code refactoring and evolution, a common challenge in long-lived software projects.

4.8.6. Comparative Analysis with Deep Learning Algorithm:

This is Code Detection Research work, where normal embedding may not be relevant as they are made for normal language conversation. Specialized embeddings that are specific python or java embeddings are needed for our, for doing further research in this domain. However, a comparative analysis with deep learning algorithm was undertaken and the following outcome was obtained:

Table 4.2 Comparative Analysis with Deep Learning Algorithm

Model	Type	Accuracy	balanced_accuracy	roc_auc	f1_score
CalibratedCV	Traditional ML	0.985	0.985	0.98985	0.985222
Ridge	Traditional ML	0.985	0.985	0.985	0.985222
LDA	Traditional ML	0.985	0.985	0.99865	0.985222
SVC	Traditional ML	0.995	0.995	0.99485	0.995025
RandomForest	Traditional ML	0.995	0.995	0.995	0.995025
GradientBoosting	Traditional ML	0.995	0.995	0.995	0.995025
MetaClassifier	Meta-Classifier	0.995	0.995	0.995	0.995025
SimpleNN	Deep Learning	0.95	0.95	0	0.955222

The evaluation results reveal several important insights about machine learning approaches for code clone detection. Traditional machine learning algorithms demonstrated exceptional performance, with SVC, RandomForest, and GradientBoosting achieving the highest accuracy (0.995) and F1 scores (0.995) among individual models. LDA showed remarkable ROC AUC performance (0.99865), indicating excellent discrimination capability between clone and non-clone code segments. While the MetaClassifier ensemble approach matched the accuracy of the best individual models. SVC offers the best balance of accuracy, making it particularly suitable for integration into developer workflows where rapid feedback is essential. The SimpleNN deep learning approach underperformed relative to traditional methods, suggesting that for this specific code clone detection task, carefully tuned traditional machine learning algorithms may be more effective than basic neural network architectures. The consistently high balanced accuracy scores across models indicate robust performance on both clone and non-clone classes, which is critical for a reliable code clone detection system that minimizes both false positives (wasting developer time) and false negatives (missing potential code duplication issues). Traditional machine learning approaches, SVC, provide the optimal balance of detection accuracy but meta-classifier (which is also based on traditional machine learning algorithms) performs better,

Corroborating the Need for Specialized Code Embeddings

The performance metrics from the code clone detection research strongly support the assertion that specialized programming language embeddings are essential for meaningful advancement in this domain. The data reveals that traditional machine learning approaches (SVC, RandomForest, and GradientBoosting) significantly outperformed the SimpleNN deep learning model (0.995 vs 0.985 accuracy), which likely stems from their reliance on hand-crafted code-specific features rather than generic embeddings.

This performance gap is clearly demonstrated , the deep learning models typically excel with appropriate representations, but the SimpleNN's underperformance shows it was

working with inadequate feature representations of code. Unlike natural language where contextual meaning dominates, code clone detection requires understanding of syntactic structures, semantic equivalence despite syntactic variations, and domain-specific patterns that general-purpose embeddings simply cannot capture.

Specialized embeddings trained specifically on Python or Java codebases may capture language-specific patterns, API usage conventions, and structural relationships that generic embeddings miss. This specialized understanding is precisely what's needed to bridge the performance gap between traditional ML approaches and deep learning methods, potentially enabling future models to surpass the already high accuracy benchmarks (0.995) established by traditional methods in our evaluation. Without such domain-specific representations, further research would be fundamentally limited in its ability to detect sophisticated code clones that vary syntactically but remain semantically equivalent.

Chapter - 5

CONCLUSIONS AND INFERENCES

5.1 Conclusion

The comprehensive analysis of code clone detection methodologies, focusing on the performance of various meta-classifier architectures, has yielded significant insights into the efficacy of ensemble learning approaches in this critical domain of software engineering. The study's findings underscore the complexity of the code clone detection task and the potential of sophisticated machine-learning techniques to address this challenge.

5.1.1 Summary of Findings

Key findings from the analysis of precision and recall values across different architectures reveal nuanced performance characteristics:

5.1.1.1 Architectural Performance

- Architectures 'A,B,C,E' and 'A,B,DE' consistently demonstrated superior precision for Class 1 (presumably non-clone code), highlighting their reliability in accurately identifying original code segments.
- The 'D,A,B' configuration excelled in precision for Class 2 (assumed to be code clones), indicating its proficiency in detecting duplicate code instances with high confidence.
- A general trend of higher precision values for Class 2 across architectures shows that the models are more adept at identifying code clones than non- clones, a favourable characteristic for practical applications.
- **Confidence in Clone Identification:** It can also be inferred that the features derived from **Abstract Syntax Trees (AST)** and **Qualitative Features of Code (QPC)** are particularly adept at capturing the subtle structural patterns characteristic of cloned code (Type-2, Type-3). This hints the model is highly effective at identifying the *presence* of duplication, which is critical for reducing false alarms in a maintenance context.

5.1.1.2 Precision-Recall Trade-offs

The analysis revealed clear trade-offs between precision and recall, a common challenge in classification tasks. This trade-off was particularly evident in varying performance across different architectural configurations.

The 'C,D,A' architecture emerged as a notable performer, achieving a commendable balance between precision and recall for both classes, suggesting its potential as a versatile solution for diverse code bases.

5.1.1.3. Individual Classifier Contributions

The study highlighted the unique contributions of each classifier in the ensemble:

- RandomForestClassifier (A) demonstrated effectiveness in mitigating overfitting, a crucial attribute for handling the diverse nature of code structures.
- Decision Tree prop (B) added an element of interpretability to the model, valuable for understanding the decision-making process in clone identification.
- Gradient Boosting (C) enhanced the overall predictive power of the ensemble, likely capturing subtle patterns in code similarity.
- Logistic Regression (D) provided a stable baseline and potentially improved the model's ability to handle linear separability in feature space.

5.1.1.4 Meta-Classifier Efficacy

The meta-classifier, constructed from these individual components, showed promising results:

- It achieved a balanced performance with a recall of 98.75% and a precision of 90.99%, outperforming individual boosting algorithms in overall effectiveness.
- This balance suggests that the meta-classifier is adept at both identifying a substantial portion of cloned instances and minimizing false positives, a critical requirement in practical code clone detection scenarios.

5.1.1.5 Limitations of the Study:

One of the issues in the research work is the balanced dataset. The dataset was carefully made sure half our examples were clones and half weren't. This helps the models learn properly, but real software doesn't work this way. In actual codebases, clones are usually much rarer - maybe only 10% or less of the code contains clones. The limitation is that perfect balance doesn't match reality, so our models might not work as well on real projects, but for making foundation models, as it is one of the new foundation models there is a need to follow this strategy.

While the model achieved a high precision of 90.99% on the balanced dataset, introducing the real-world scarcity (e.g., 10% clone prevalence) requires quantitative caution. We acknowledge that the Positive Predictive Value (PPV) is theoretically sensitive to prevalence shifts. If the model were deployed in a production environment with a clone rate below 10%, the current precision metric, which was established under optimal training conditions (50% prevalence), may experience degradation, potentially leading to an elevated False Positive Rate (FPR) in practice.

The experiments were performed on consumer hardware (Intel Core i5-1135G7, 16 GB RAM) without dedicated GPU acceleration. This configuration meant that complex neural network operations, including those for CodeBERT, were executed on the CPU, significantly impacting processing speed. We quantify this limitation by noting that deploying the meta-classifier, which involves training multiple base classifiers (ensemble method), introduces an inherent higher computational overhead compared to using a single, optimized boosting algorithm,. This limits the current version's scalability to millions of lines of code without parallelization.

The current data extraction relies heavily on Python's built-in ast module. The limitation of solely testing on Python CLI tools means we cannot quantitatively predict the Recall degradation (False Negative Rate) when faced with languages featuring radically different structural features (e.g., Java’s curly braces and explicit typing versus Python’s indentation). The proposed future transition to a universal parser like tree-sitter is the quantitative step necessary to enable language-agnostic feature extraction and validation

Finally, the next limitation is large scale generalization of the outcomes and results of the model The data comes only from popular Python command-line projects on GitHub. This implies the system might work great on Python CLI tools but fail completely on Java web applications or C++ game code. Also, by only using projects with many stars, less popular projects were ignored that might have different coding styles but for the sake of this research repositories that are professional in nature, live and maintenance were preferred.

5.1.1.6 Practical Implications

- The meta-classifier's performance positions it as a robust solution for real-world software development environments, where both high recall (to catch most clones) and high precision (to minimize false alarms) are crucial.
- Its balanced approach addresses the need for efficient code review processes and effective management of code quality and maintainability.

5.1.2 Novelty and Contributions of the Research

The primary research contribution can be summarized as follows:

In this research a design of a robust framework for evaluating code clone detection with realistic data, and through a comprehensive analysis was done, it was discovered that a well-tuned meta classifier is the most robust and efficient solution, outperforming complex deep learning models.

This contribution is supported by three key pillars:

5.1.3 A More Realistic Evaluation Framework

Programmatic Code Mutation: A `code_mutator.py` script was developed to programmatically generate realistic Type-2 and Type-3 code clones by modifying the Abstract Syntax Tree (AST). This creates a more challenging and practical benchmark compared to using simple, identical code duplicates.

Challenging Negative Pairs: The dataset was improved by creating negative (non-clone) pairs from files within the same repository, increasing their similarity and

making the classification task more difficult and realistic.

5.1.4 Comprehensive Benchmarking

Wide Spectrum of Models: The framework was used to rigorously evaluate a wide range of models on the same robust dataset, including traditional machine learning classifiers, deep learning models (CodeBERT, SimpleNN), and a custom-built stacking ensemble (meta-classifier).

5.1.5 Direct, Empirical Comparison: This head-to-head comparison provides a clearand valuable performance benchmark across different model families. The key finding is that the `Metaclassifier` delivers state-of-the-art performance, matching the accuracy of a methods. This result challenges the assumption that larger, more complex models are always better. It demonstrates that with robust feature engineering, computationally efficient models can be the superior choice for specific, real-world tasks like code clone detection, providing significant value in terms of cost and complexity.

5.2 Future Directions

Based on the current implementation and the limitations identified, several concrete future directions can be pursued to enhance the capabilities and realism of the code clone detection system.

5.2.1 Advanced Deep-Learning Hybrid Models

While the existing plan includes expanding the HybridFusionModel, this direction should be strengthened by explicitly focusing on developing and leveraging specialized domain-specific code embeddings.

- Necessity of Specialized Embeddings: The performance analysis comparing the custom meta-classifier to the simple neural network (SimpleNN) demonstrated that deep learning approaches currently underperform compared to traditional ML techniques that rely on hand-crafted features,. Future work is required to bridge this gap by developing specialized Python or Java embeddings that capture language-specific patterns and structural relationships, which generic embeddings miss.

- Richer Semantic Capture: This expansion should include exploring more sophisticated architectures that capture richer semantic features by explicitly incorporating embeddings derived from code comments and variable names into the model.

5.2.2 Cross-Language Clone Detection

The objective of supporting multiple programming languages remains crucial.

- Universal Parsing Implementation: Future work should prioritize the implementation of a universal parser, such as tree-sitter, to replace the language-specific Python ast module. This would create language-agnostic representations necessary to support parsing a wider variety of languages (e.g., JavaScript, Java, C++, Go).
- Multi-Lingual Model Foundation: This foundational work would enable the development of multi-lingual deep learning models capable of identifying cross-language clones.

5.2.3 Adaptation for Real-World Imbalanced Data

This new direction directly addresses a critical limitation noted in the Conclusion regarding dataset generation.

- Addressing the Reality Gap: The current evaluation used a carefully balanced dataset, but real-world codebases typically have clones that are "much rarer" (maybe 10% or less). Therefore, a necessary future research direction is to focus on evaluating and adapting the meta-classifier's performance for highly imbalanced datasets. This would involve studying specialized loss functions or resampling techniques to ensure robustness when clones are rare.

5.2.4 Integration of Hybrid Ensemble Methodologies

This new direction leverages the comparative analysis conducted in Chapter 4.

• Combining Stacking and Boosting Strengths: The comparative analysis revealed that while the stacking meta-classifier achieved a high, balanced performance (Recall of

98.75% and Precision of 90.99%), individual boosting algorithms like LightGBM and XGBoost demonstrated even higher recall (99.06%),. Future work should investigate advanced hybrid ensemble architectures that integrate the high recall achieved by boosting methods with the balanced precision of the stacking approach, potentially creating an even more robust and adaptable system.

5.2.5 Industrial Case Study and Usability Evaluation

This area remains essential for transitioning the research into practical application.

- Scalability and Validation: Future work must include collaboration with a software company to conduct a real-world evaluation of the system's performance and scalability on large-scale, proprietary codebases.
- Integration and Developer Workflow: The study should incorporate a usability study focused on how the tool can be integrated into existing developer workflows and systems, such as IDEs or code review systems, to ensure it provides actionable insights for effective code quality management

In conclusion, this study demonstrates the potential of advanced machine learning techniques, particularly ensemble methods and meta-learning approaches, in significantly improving the accuracy and reliability of code clone detection. The developed meta-classifier, with its balanced performance profile, represents a significant step forward in addressing the challenges of code duplication in large-scale software projects. As software systems continue to grow in complexity and scale, such sophisticated clone detection tools will play an increasingly crucial role in maintaining code quality, enhancing software maintainability, and ultimately improving the efficiency of software development processes.

The findings of this research not only contribute to the theoretical understanding of applying machine learning to software engineering problems but also offer practical tools and insights for developers and organizations striving to manage and improve their codebases effectively. As the field evolves, the integration of such intelligent code analysis tools into standard development workflows promises to revolutionize how we approach software quality and maintenance in the digital age.

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List of Publications

[1] “Adaptive Prefix Filtering for Accurate Code Clone Detection in Conjunction with Meta-Learning", to be published in SN Computer Science journal, indexed in Scopus, Web of Science, [Current Status-Accepted, to be published]

[2] C. Ralhan and N. Malik, "A Study of Software Clone Detection Techniques for Better Software Maintenance and Reliability," 2021 International Conference on Computing Sciences (ICCS), Phagwara, India, 2021, pp. 249- 253, doi: 10.1109/ICCS54944.2021.00056.

List of Conference Attended

[1] 6th International Joint Conference on Computing Sciences (ICCS) "BOOTH100" held on 11th November 2022 held at Lovely Professional University.

[2] 5th International Conference on Computing Sciences (ICCS) "Kathleen 100" held on 4-5th December 2021 held at Lovely Professional University.