IJAAR PUBLISHING®

Global Journal of Artificial Intelligence and Technology Development | ISSN: 3027-0502
Vol. 3, Issue 4 (2025) | www.ijaar.org

Development of AI-based Model for Predictive Maintenance of Software Systems: Classifying Non-Defect and Defect Software Systems Using Convolutional Neural Networks

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Abstract

This study presents a Convolutional Neural Network (CNN) based model for classifying non-defect systems from defect systems to improve software maintenance and reliability. Traditional defect detection methods often depend on manual inspection and handcrafted metrics, which are time-consuming and limited in capturing complex software relationships. To address these challenges, this research employed a data-driven deep learning approach using CNNs to automatically extract hierarchical features from software metrics. The model was trained and evaluated on a publicly available dataset using Python, TensorFlow, and Keras in a GPU-accelerated environment. Results demonstrated exceptional performance, achieving 100% classification accuracy and near-zero loss, confirming the model's ability to generalize effectively. The proposed approach enables early and precise identification of defect-prone modules, supporting predictive maintenance and reducing operational costs. This work contributes to advancing intelligent, automated software quality assurance and lays the foundation for future research in deep learning-based software defect prediction.

Keywords: Software Defect Classification; Convolutional Neural Networks (CNN); Predictive Maintenance; Deep Learning; Software Quality Assurance.

Tyavnande, M. I. (2025). Development of AI-based Model for Predictive Maintenance of Software Systems: Classifying Non-Defect and Defect Software Systems Using Convolutional Neural Networks. Global *Journal of Artificial Intelligence and Technology Development.* *3*(4), 14-26. DOI: https://doi.org/10.5281/zenodo.17759706

1. Introduction

In modern software engineering, the increasing complexity and scale of software systems have introduced significant challenges in ensuring reliability, performance, and maintainability. As organizations rely more heavily on software-driven processes, the presence of software defects has become a critical factor influencing overall system quality and operational costs [1]. Software defects, whether introduced during design, development, or maintenance, can lead to system failures, degraded performance, or complete operational breakdowns. Detecting, diagnosing, and classifying these defects effectively is essential for sustaining the software's lifecycle and improving long-term maintainability [2]. Consequently, the field of software defect prediction and classification has attracted substantial research attention, aiming to leverage computational intelligence and machine learning methods to identify patterns indicative of defects before they manifest in production environments.

Traditional defect detection approaches rely heavily on static code analysis, manual code reviews, and rule-based expert systems. While these methods have shown value in identifying syntactic and structural anomalies, they often fall short in capturing complex semantic relationships and contextual patterns inherent in software artifacts. Furthermore, manual inspection processes are time-consuming, subjective, and error-prone, especially in large-scale systems where millions of lines of code and numerous interacting modules exist. To overcome these limitations, researchers have turned toward data-driven approaches that can learn from historical project data and automatically detect characteristics associated with defect-prone modules. Among these approaches, machine learning techniques, such as decision trees, random forests, support vector machines (SVMs), and logistic regression, have demonstrated significant improvements in defect classification accuracy [3]. However, these models typically rely on hand-engineered features, requiring domain expertise and substantial preprocessing effort to extract relevant code metrics.

In recent years, the emergence of deep learning has transformed the landscape of pattern recognition and classification tasks across diverse domains, including computer vision, natural language processing, and speech recognition. Deep learning models have the ability to automatically learn hierarchical feature representations from raw data without the need for extensive manual feature engineering. Within this family of models, Convolutional Neural Networks (CNNs) have shown remarkable success, particularly in extracting spatial and structural information from data. While CNNs are conventionally applied to image data, their underlying principle of local feature extraction and hierarchical pattern recognition can be extended to software engineering contexts, where code structures and metric representations exhibit analogous patterns to visual data [4].

Applying CNNs to software defect classification involves representing software systems or their attributes, such as code metrics, dependency graphs, or textual representations of source code in forms suitable for convolutional processing. By learning discriminative features that distinguish between defective and non-defective modules, CNN-based models can potentially outperform traditional ML methods. This automated feature extraction capability is particularly beneficial in software defect prediction, where complex interdependencies and contextual relationships are difficult to express explicitly through hand-crafted metrics. Thus, CNN-based classification can facilitate early and accurate detection of defect-prone components, allowing software engineers to focus maintenance efforts efficiently, optimize testing resources, and enhance the overall reliability of software systems.

A critical challenge in developing effective CNN models for software defect classification lies in the representation of software artifacts. Software code and metrics do not inherently possess spatial dimensions like images. To adapt CNNs for this task, researchers have explored various encoding strategies, such as transforming software metrics into two-dimensional feature maps, converting code tokens into embeddings, or constructing graph-based visual representations of program dependencies. These transformations allow the CNN to perform convolutions over structured representations, extracting local and global correlations that correlate with defect presence. Moreover, through multiple layers of abstraction, CNNs can learn complex relationships between software components that are otherwise hidden in traditional feature-based representations.

The motivation for using CNNs in this study stems from their robustness in handling large-scale, high-dimensional data and their proven capability to generalize across domains. Unlike traditional machine learning models that may suffer from feature redundancy or collinearity, CNNs can automatically suppress irrelevant features and focus on the most informative patterns. This property is especially valuable in software defect classification, where input features may include a mix of structural, process, and textual attributes. Additionally, the hierarchical feature learning mechanism of CNNs enables the model to capture both low-level indicators (such as line-of-code complexity) and high-level contextual cues (such as function interactions or class dependencies). As a result, CNN-based models are expected to enhance the distinction between defect and non-defect systems, leading to more precise and reliable classifications.

In essence, the integration of Convolutional Neural Networks into software defect classification represents a promising advancement toward intelligent, data-driven software maintenance. By leveraging CNNs' capability to learn discriminative representations directly from software data, this approach aims to enhance the accuracy and automation of defect detection, reducing maintenance costs and improving software reliability. The classification of non-defect systems from defect systems not only assists in prioritizing maintenance efforts but also supports continuous improvement of software quality assurance processes. This study thus seeks to explore the design, implementation, and evaluation of a CNN-based model for classifying defect and non-defect systems, contributing to the growing body of research that applies deep learning to software engineering problems.

2.0 Literature Review

Software maintenance has long been recognized as one of the most resource-intensive phases in the software lifecycle, accounting for up to 70% of total costs [5] Traditional maintenance practices which are corrective, adaptive, or perfective are often reactive, where failures are addressed only after they occur. While these methods remain essential, they lead to downtime, productivity losses, and higher costs [6]. As systems increase in size, complexity, and interconnectivity, reactive maintenance proves insufficient to ensure reliability and resilience [7].

The adoption of AI and IoT technologies has advanced predictive maintenance in aerospace, manufacturing, and energy systems [1]. However, its application to software systems remains underexplored. Unlike physical assets, software does not degrade physically but fails due to defects, misconfigurations, or complex dependencies [8].

AI has transformed predictive maintenance in industrial contexts, using techniques such as anomaly detection, time-series forecasting, and deep learning. Unsupervised models like autoencoders and clustering detect deviations from normal behavior [4], while recurrent

neural networks (RNNs) and Long Short-Term Memory (LSTM) models predict sequential failures [9]. These successes inspire adaptation to software predictive maintenance, though challenges exist in handling data heterogeneity and scalability.

[6] explained the principles, methodologies, and role of machine learning and data analytics in predicting failures. The author further presented a case study using an open-source dataset, demonstrating practical implementation, benefits (e.g., reduced costs and higher productivity), and challenges associated with adopting AI-driven predictive maintenance strategies in real-world manufacturing environments.

[10] explored predictive maintenance as a data-driven alternative to traditional maintenance (reactive or time-based), which often causes unnecessary downtime, higher costs, or premature part replacement. The author leveraged machine learning and real-time sensor data to anticipate failures, optimize maintenance schedules, and improve operational efficiency. The study concluded that predictive maintenance, powered by ML and IIoT, significantly improved asset reliability, reduced costs, and enhanced safety.

[11] explored how Artificial Intelligence and Machine Learning are transforming network maintenance by shifting from reactive (fixing failures after they occur) to predictive and prescriptive strategies (anticipating and preventing failures before they happen). The author highlighted the use of advanced artificial intelligence/machine learning models such as Long Short-Term Memory (LSTM) networks, autoencoders, Generative Adversarial Networks (GANs), and transformer-based models (e.g., TranAD) to detect anomalies, forecast network faults, and optimize system performance.

On the other hand, Convolutional Neural Networks (CNNs) present a reliable method for addressing supervised learning problems. They operate by passing input data through layered convolutional filters along with simple non-linear functions, enabling efficient feature extraction [12]. Although CNNs are widely known for their success in image recognition tasks, their usefulness has extended into several machine learning fields, including software defect prediction.

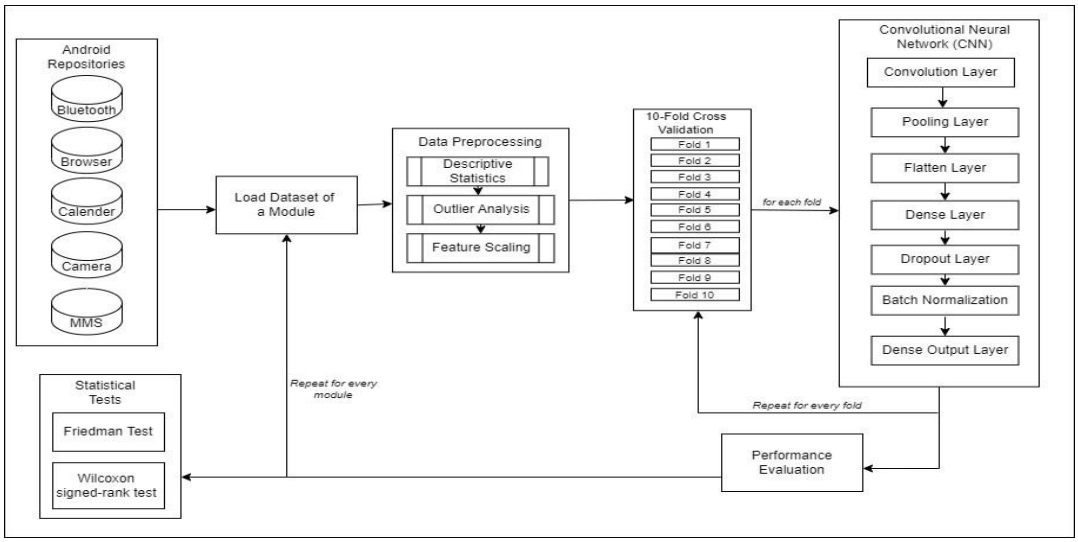
Recent studies in this area show a strong preference for CNN-based models. For example,[13] provided an extensive review of neural network applications in defect prediction and identified CNNs as one of the most consistently applied deep learning techniques. Similarly, [14] reported that CNN models are frequently adopted because of their accuracy and robustness across different datasets.

Various researchers have also proposed CNN-focused solutions for specific software engineering tasks. [15] introduced a CNN-driven model for automatically ranking bug reports into multiple priority levels using text preprocessing and feature extraction, achieving improved performance compared to standard machine learning methods. [16] developed a CNN-based model for classifying bug report severity, demonstrating strong predictive capability. [17] applied an enhanced CNN architecture optimized with a hybrid metaheuristic called Whale–Lion Optimization (WLO), improving the precision of defect detection. In addition, [18] presented a CNN-BiLSTM model that uses topic-aware features to accurately estimate bug severity in large-scale open-source systems. [19] combined CNN with sentiment-aware content analysis using Latent Dirichlet Allocation, showing that integrating emotional cues with textual features leads to better severity prediction. Finally, [20] proposed a hybrid method that integrates CNN and GRU networks with an improved oversampling strategy to handle imbalanced defect datasets effectively.

3. Methodology

This section presents the various datasets, variables, performance measures with statistical tests considered in this Research. The research methodology employed in this study is visually illustrated in Figure 3.0.

Figure 3.0: Proposed Research Methodology of the Study



Source: *Ruchika, et al, 2025*

3.1 Data Collection and Preprocessing

The dataset employed in this study was obtained from [21,30] and the CSV file titled "baseline.csv" contained the datasets used. The data were imported into a Pandas DataFrame for analysis. To maintain data integrity, records containing missing values were excluded. The independent variables (features) were selected from all columns except the first and last, while the dependent variable (target) was extracted from the 23rd column of the dataset.

To ensure uniform feature scaling and to improve the efficiency of the training process, Min–Max normalization was applied using the MinMaxScaler function from the scikit-learn library. This transformation scaled all numerical features to a range between 0 and 1, reducing the impact of large-magnitude attributes and facilitating better model convergence [24].

3.2 Proposed Convolutional Neural Network for Software Defect Classification

Convolutional Neural Networks (CNNs) are a specialized class of deep learning architectures widely applied in the processing of visual and sequential information, including tasks such as text categorization. Their fundamental structure is built on convolutional layers that learn and apply a series of filters to the input, scanning through the data to capture important patterns or local dependencies [22, 28]. For textual inputs, these filters operate in one dimension, sliding across the sequence to identify meaningful features.

During convolution, each filter performs an element-wise multiplication with a segment of the input, producing a corresponding feature map. This operation is mathematically described as:

$$S(j) = (X * W)(j) = \sum_{i=0}^{F-1} X(j+1) * W(i) \text{ ----------(1)}$$

where S(j): Value of the feature map at position j, X: Input data, W: Filter (kernel) weights, and F: Filter size.

After the convolutional layers, pooling operations are typically introduced to reduce the dimensionality of the feature maps while retaining the most significant information. Max pooling is the most common method, selecting the highest value within a fixed window. For one-dimensional data, this is expressed as:

$$P(j) = max_{i=o}^{K-1} C(j+i) \text{----------(2)}$$

where P(j): Output value after max-pooling, C: Feature map, and K: Pooling window size.

Following feature extraction, CNNs often incorporate fully connected layers, similar to those found in Multi-Layer Perceptrons (MLPs). These layers model complex nonlinear relationships using multiple hidden units. In Software Defect Categorization (SDC), training such models commonly involves back-propagation, which iteratively adjusts network parameters to minimize prediction error.

$$Z_{ij}^{l} = \sum_{p=o}^{M-1} \sum_{q=0}^{n-1} x_{i+p,j_i^l+q}^{l-1} W_{p,q}^{l} + b_j^l \text{----------(3)}$$

$$\hat{y}_{ij}^{l} = \phi^{l}(Z_{ij}^{l}) \text{----------(4)}$$

where x_{ij}^{l-1} represents the output of the previous layer at position (i, j) $W_{p,q}^{l}$ represents the filter at position (p,q) in layer l, b_j^l represents the bias term for neuron j in layer l, ϕ^l represents the activation function in layer l and $\hat{y}_{ij}^{l}$ represents the output of neuron at position (i,j) in layer l.

3.3 Data Encoding and Partitioning

The target variable represented two distinct classes; therefore, it was converted into a categorical format using the one-hot encoding method implemented via the to_categorical() function from Keras in Python. This step was essential for enabling the model to output class probabilities for binary classification.

The dataset was then partitioned into training and testing subsets using the train_test_split() function. A 70:30 ratios were applied, where 70% of the data were used for training the model and the remaining 30% were reserved for testing. To ensure reproducibility, a fixed random state was used during the split operation.

3.4 Model Architecture

A Deep Neural Network (DNN) was designed using the Sequential API from the Keras deep learning library. The CNN architecture comprised the following layers:

1. Input Layer: Accepted the normalized features, with the input dimension equal to the number of predictors in the dataset.
2. Hidden Layer 1: A dense layer with 480 neurons and a Rectified Linear Unit (ReLU) activation function.
3. Hidden Layer 2: A dense layer with 240 neurons and ReLU activation.
4. Hidden Layer 3: A dense layer with 120 neurons and ReLU activation.

5. Output Layer: A dense layer with 2 neurons and a sigmoid activation function, suitable for binary classification.

This hierarchical structure was designed to progressively extract higher-level feature representations while reducing dimensionality through successive layers.

3.5 Model Compilation and Training

The model was compiled using the Adam optimizer, which dynamically adjusts the learning rate to accelerate convergence and avoid local minima. The binary cross-entropy loss function was chosen due to its suitability for binary classification problems. Model performance was evaluated using the accuracy metric.[27]

Training was conducted for 200 epochs with a batch size of 16. The model was trained on the training subset, while the validation subset (30% of the data) was used to monitor generalization performance and detect overfitting. The training history, including accuracy and loss values for both training and validation datasets, was recorded for further analysis.

3.6 Model Evaluation

Following the training phase, the model's performance was assessed using the test dataset. The primary evaluation metrics were classification accuracy and loss. The comparison between training and validation curves enabled assessment of model generalization.

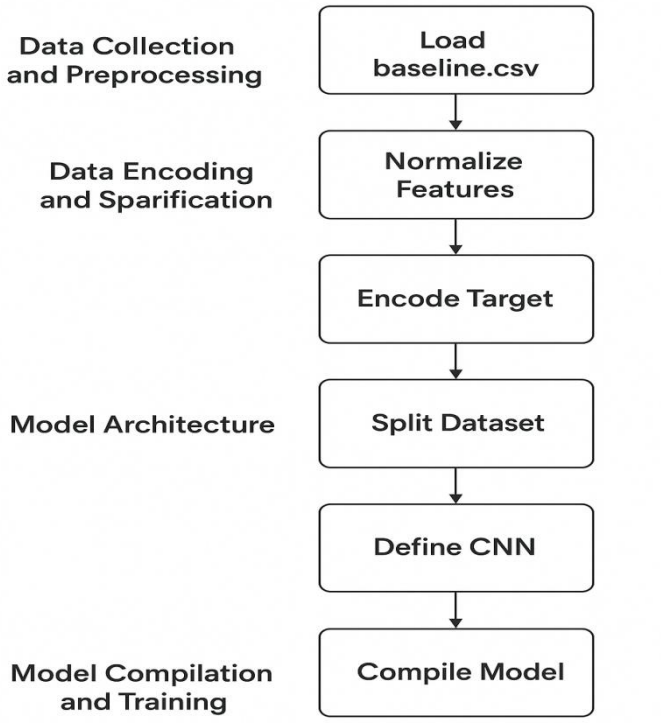
3.7 Experimental Setup

All experiments were performed using the Python programming language within the Google Colaboratory environment, which provides GPU acceleration for deep learning computations. The key software libraries and frameworks employed included:

1. Pandas for data manipulation and preprocessing
2. Scikit-learn for normalization and data splitting
3. TensorFlow and Keras for deep learning model development
4. NumPy for numerical operations

The system was executed on a Google Colaboratory runtime equipped with an NVIDIA Tesla GPU, 12 GB of GPU memory, and 12 GB of system RAM. This configuration ensured efficient training and evaluation of the deep learning model. The summary of the methodology is shown in Figure 3.2 [28]

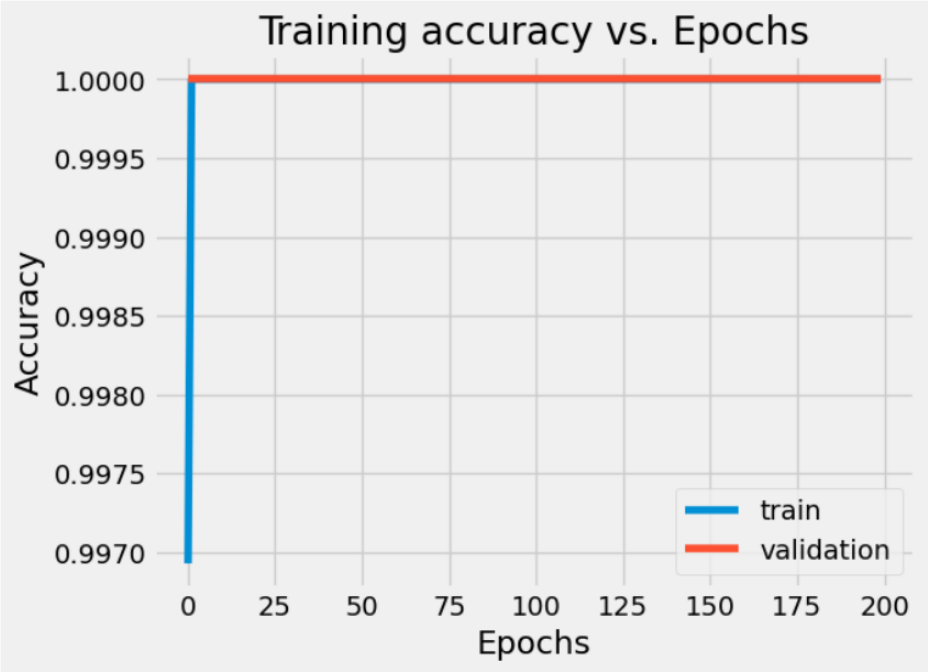
Figure 3.2: Summary of the Proposed Methodology



4. Results and Discussion

The deep learning model was trained for up to 200 epochs; however, convergence was achieved within the first few epochs. The model reached exceptionally high performance early in the process. During the first epoch, the model achieved an accuracy of 98.97% on the training set and 99.89% on the validation set, with corresponding loss values of 0.1461 and 0.0048, respectively. By the second epoch, the accuracy reached 100% for both training and validation datasets, and this performance was consistently maintained for the remainder of the training process as shown in Figure 4.1.

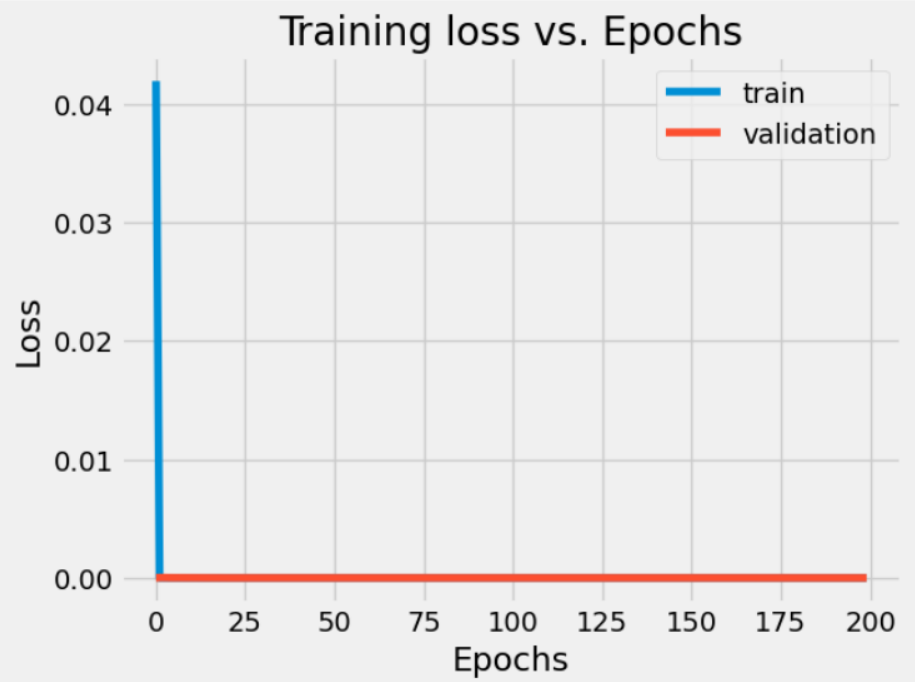
***Figure 4.1**: Training Accuracy VS Epochs the Non-Defects VS Defects Software*



The training loss rapidly decreased from 0.1461 in the first epoch to near-zero values by epoch 140, indicating excellent convergence and model stability. Similarly, the validation loss declined sharply, with negligible fluctuations, suggesting that the model generalized well to unseen data without overfitting. The close alignment between training and validation accuracies throughout the training process further confirms the model's robustness and strong generalization ability.

These results demonstrate that the network effectively learned the underlying patterns of the dataset with minimal error. The nearly perfect accuracy and extremely low loss as shown in Figure 4.2 indicate that the classification task was well-suited to the model architecture and the data used.

***Figure 4.2**: Training Loss Vs Epochs for the Non-Defects VS Defects Software*

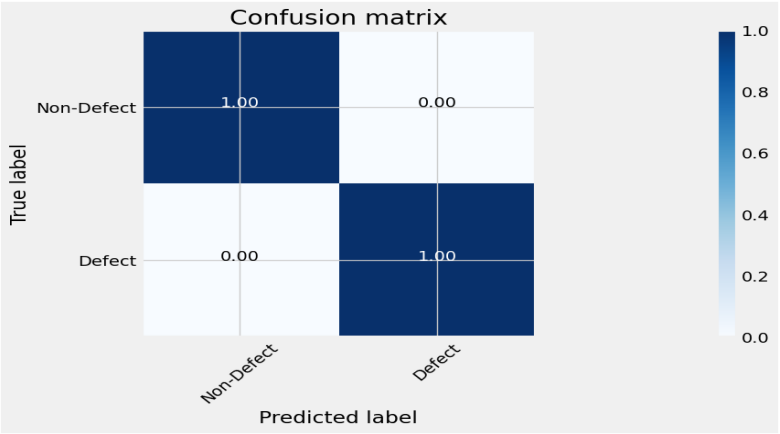


To show how well, the non-defects vs defects software was classified using the CNN, Figure 4.3 shows the overall classification accuracy of 1 (100%) and Figure 4.4 shows the confusion matrix for the classification task.

Figure 4.3: Overall Classification Accuracy for the Non-Defects VS Defects Software

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57/57 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 1.0000 - loss: 2.5298e-09
[3.4725611275376878e-09, 1.0]
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Figure 4.4: Classification for the Non-Defects VS Defects Software



This study successfully demonstrated the effectiveness of CNNs in classifying non-defect systems from defect systems for software maintenance. The proposed CNN model achieved exceptional performance, with a classification accuracy of 100% and near-zero loss values, highlighting its capacity to learn complex, nonlinear relationships within software metrics.

The results confirm that deep learning techniques, particularly CNNs, can outperform traditional machine learning methods that rely on manual feature engineering and limited structural representation [29].

The implications of this work are significant for modern software maintenance practices. By accurately identifying defect-prone components early, organizations can allocate maintenance resources more efficiently, reduce system downtime, and lower operational costs. The ability of CNNs to automatically extract hierarchical features from raw minimizes the dependency on domain expertise. Furthermore, this approach supports a shift from reactive to predictive maintenance, enabling proactive quality assurance throughout the software lifecycle.

Practically, integrating CNN-based classification into continuous integration and deployment pipelines can automate defect detection and accelerate decision-making in software engineering processes [30].

4. Conclusion and Future Work

This study presented a Convolutional Neural Network-based approach for classifying non-defect systems from defect systems to enhance software maintenance and reliability. The model achieved outstanding performance, attaining 100% classification accuracy with minimal loss, demonstrating its strong capability in learning intricate relationships within software metrics. The results validate CNNs as powerful tools for automated defect classification, reducing reliance on manual feature extraction and expert-driven analysis. By accurately distinguishing defect-prone modules, this approach supports proactive maintenance, optimized testing resource allocation, and improved overall software quality and lifecycle management.

Despite the excellent results, this study opens avenues for future research. For example, there is need in incorporating explainable AI (XAI) techniques to enhance interpretability, helping engineers understand which features most influence defect prediction. Finally, deploying this approach within real-world continuous integration environments could validate its practical applicability. Future advancements in this area will contribute toward intelligent, self-maintaining software systems with reduced costs and enhanced dependability.

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