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Small Metal Objects Classification Based on The Deep Learning Approach

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ABSTRACT

Classification of small metal objects plays a crucial role in various engineering fields, including manufacturing, robotics, and security. With advancements in deep learning techniques, the use of Convolutional Neural Networks (CNNs) has emerged as a powerful tool for image classification tasks. The methodology begins by collecting diverse datasets consisting of images of small metal objects. The datasets are labelled with corresponding object classes to facilitate supervised learning. Preprocessing techniques like re-sizing, normalization, and augmentation are used to improve the quality and diversity of the datasets. The use of CNNs in classification can be a better option compared to commonly used machine learning approaches. The CNN architecture is designed and trained to learn the distinguishing features of small metal objects. The main objective of this study is to assess the accuracy of this classification and explain how CNNs can enhance classification accuracy. The results of this study also show the effect of the optimizer on the classification process, which changes when different types of optimizers such as RMSprop, Adam, and SGD are used. While some optimizers yield slightly lower accuracy results, the Adam optimizer with the CNN ResNet-50 module proves suitable for use with this dataset, achieving a high classification accuracy of 86%.

Keywords: Small metal classification, deep learning, small metal object

1. INTRODUCTION

Sorting parts is a crucial approach for manufacturing companies to enhance part reusability and minimize part counts. However, it remains a challenging task for numerous manufacturing enterprises. The large number of spare parts creates a management challenge for the company. Additionally, engineers will inevitably face time and labour-intensive tasks when selecting the appropriate parts from such a vast array. Conventionally, automated parts sorting management plays a key role in streamlining user access, increasing the rate of part re-usability, minimizing part quantity, increasing efficiency and reducing the ever-increasing cost and time associated with new parts development. The classification of parts and components offers advantages across various stages such as design, processing, procurement, and manufacturing. Regarding design, an efficient parts sorting system enables engineers to promptly locate suitable or analogous parts for direct reuse. Alternatively, it allows for design enhancements by leveraging similar components, thereby boosting design efficiency.

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In the case of quality parts sorting, the process begins with a quality type where non-conforming parts are either designated as obsolete or repaired according to established OEM quality standards, depending on the nature of the damage or defect.

Rework or waste management includes collection, transportation, processing, disposal, and monitoring. Usually, for parts with complex defects, Comprehensive Logistics will request to rework the part. This rework process is usually done manually by the rework team. However, sometimes, the quality of the reworked part is affected during the rework. Typically, a manual inspection approach is used to check the condition of a part before it can be reused. The recovered metal serves as a valuable resource for various industries. Scrap metals can be recycled, preserving resources and reducing energy consumption [5]. Various industries impact waste quality and quantity. Various techniques have been applied such as manual sorting, magnetic separation, and eddy current separation are used for scrap metal separation [6].

By utilizing advanced machine learning techniques, objects can be automatically classified and categorized into various groups using deep learning. This research is focusing on the small metal objects classification since it is crucial to identify the damage on the small metal object and to classify it based on size and shape. However, developing a standardized classification system for small metal objects is challenging due to their wide range of sizes and shapes [3]. The sorting procedures often require significant labour and are inefficient due to the irregular shapes and intricate features of these objects. Implementing appropriate strategies, such as data augmentation, transfer learning, robust feature extraction, ensemble methods, and addressing class imbalances, can enhance the accuracy and efficiency of small metal object classification systems, thereby increasing their reliability [4].

The classification involves supervised learning techniques using machine learning algorithms like Decision Trees, Naive Bayes, and Linear Regression [6]. Deep learning, a subset of machine learning, employs neural networks, particularly Convolutional Neural Networks (CNNs), for image classification tasks. CNNs are trained on large labelled datasets to learn intricate features and patterns for accurate object classification [7]. Deep learning for small metal object analysis faces challenges due to limited labelled data, lack of visual diversity, complex designs, and various angles. Deep learning models can struggle with generalization and real-time processing. Overcoming these challenges requires techniques like data augmentation, transfer learning, inclusion of domain-specific knowledge, and multi-modal learning. Enhancements include data augmentation to increase diversity, transfer learning for efficient learning, incorporation of domain-specific knowledge, and multi-modal fusion techniques. Experimentation and fine-tuning are crucial to identifying optimal strategies for specific scenarios [8].

Thus, the study aims to classify small metal objects using CNN classifiers, considering the accuracy of the classification. CNNs offer automated feature extraction, making them suitable for direct use with raw data. The research explores CNN's potential in small metal object classification, as this approach is less commonly used in this domain [9].

2. SMALL METAL OBJECT CLASSIFICATION APPROACH

Classification of Small Metal Objects with a Deep Learning Approach is necessary to achieve efficient and accurate classification, standardize processes, increase productivity, gather valuable insights, ensure consistent quality control, reduce costs and contribute to technological progress. It addresses the challenges associated with manual classification and provides many benefits across various industries dealing with small metal objects. For that purpose, an experiment was conducted to collect data for object classification.

Datasets for small metal objects were created through personal experimentation, containing 2500 images of different metal types. These datasets include images of coins, keys, paper clips, nuts, and screws, with 500 images for each category. These images are used for classification analysis. Data collection encompasses the process of acquiring information from small metal objects, emphasizing both quality and relevance. Through meticulous planning, potential biases are minimized, integrity is upheld, and privacy is maintained. The experiment conducted in this context entailed gathering data about small metal objects utilizing cameras. For this study, keys, coins, nuts, paper clips, and screws were utilized to represent the small metal objects.

The adoption of a white background aimed to reduce image noise. Figure 1 shows the experiment setup for this study. The process of data collection entails the acquisition of information from small metal objects, with a focus on maintaining quality and relevance. Through meticulous planning, biases are mitigated, integrity is upheld, and privacy is safeguarded. Data preprocessing encompasses the transformation of raw data into a suitable format that can be effectively utilized by machine learning algorithms. The images obtained from the collection of small metal objects underwent preprocessing steps, including cropping and resizing, facilitated by MATLAB, for data augmentation. Subsequently, the resized images were systematically organized into distinct folders corresponding to their respective class labels. Table 1 provides an overview of the types and quantities of small metal objects employed in this study, with class labels denoting the data types as indicated in the table.

Table 1 Number of Samples for Each of Small Metal Object

Object Type		No. of samples
Key (K)		500
Nut (N)		500
Paper Clip (P)		500
Screw (S)		500
Coin (C)		500
	TOTAL	**2500**

Figure 1. Experiment setup for data collection

The classification process parameters are configured, with a focus on altering the optimizer in this study. The initially utilized ResNet-50 model will be substituted with a CNN model. The datasets will undergo training using the CNN model, employing an appropriate number of epochs, and the training process is expected to conclude within a few minutes. Upon the successful completion of the training process, three classification outputs will be generated: accuracy and loss graphs, a comprehensive data overview, and a confusion matrix. The implementation of the Small Metal Object Classification with a Deep Learning Approach necessitates a flowchart project. Convolutional Neural Networks (CNNs) are employed for classification. The architecture and design of CNNs, including Convolution, Pooling, and Fully Connected layers, are discussed. The application of the ResNet-50 model to improve classification accuracy is highlighted.

In conclusion, accuracy, recall, F1-score, and the confusion matrix are crucial metrics to take into account when assessing the performance of a model trained to classify small metal objects using a Convolutional Neural Network (CNN). Recall evaluates the model's capacity to identify all occurrences of positives, while precision measures the accuracy of positive predictions, and the F1-score provides a balanced assessment of the model's performance. The model's overall performance can be evaluated using the confusion matrix, which provides comprehensive information about the model's true positives, true negatives, false positives, and false negatives. All of this information will first be saved as a PNG picture file. The emphasis will be on classifying small metal objects, and the results will be documented and discussed in the following chapter. A classifier is provided with the datasets for classification training and testing. Convolutional Neural Network (CNN) technology will be used to categorize the data. Figure 2 illustrates the process to accomplish Small metal object classification approach.

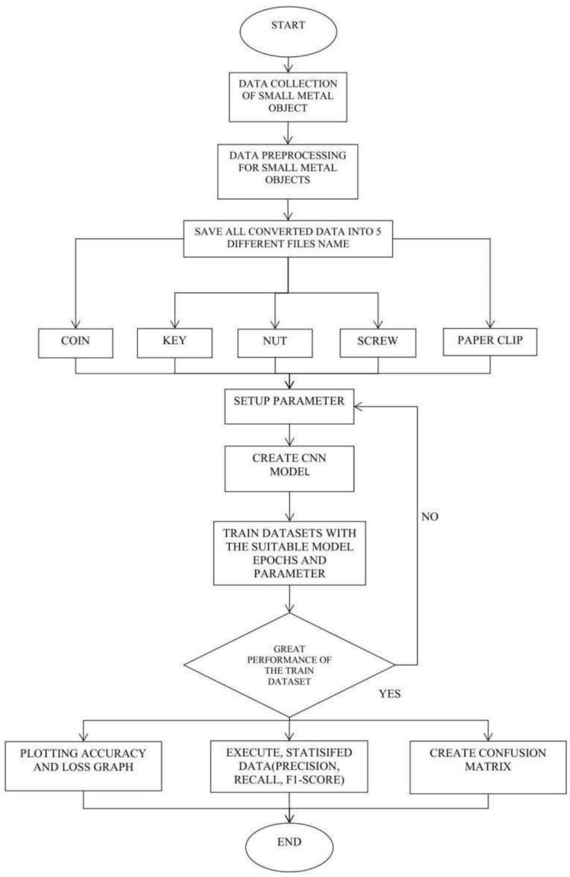

Figure 2. Small metal object classification approach

3. RESULT AND DISCUSSION

The classification outcome is based on datasets of small metal object images. In this study, we employ the Convolutional Neural Network (CNN) deep learning method, thus the focus of the outcome will be on this area. The performance evaluation of various types of optimizers has been compared and discussed in the subsequent sub-chapter.

3.1 Result with Optimizer Adam

The testing and training are conducted using a Google Collaboratory server. The CNN model ResNet-50 classifier is tested using the Small Metal Object Image datasets. The goal of this research is to determine the values of the F1-score, recall, accuracy score, and any other associated outputs. These classification processes were applied with different deep-learning optimizers, and data on precision, recall, and F1-scores were collected [10]. Table 2 shows Execute Satisfied Data (Precision, Recall, F1-score) for Optimizer Adam.

Table 2 Execute Satisfied Data (Precision, Recall, F1-score) for Optimizer Adam

Small Metal Objects	Precision	Recall	F1-score	Support
Coin	0.84	0.99	0.91	100
Key	0.72	0.81	0.76	100
Nut	1.00	1.00	1.00	100
Screw	0.98	0.49	0.65	100
Paper Clip	0.84	1.00	0.91	100
Accuracy			0.86	500
Macro avg	0.88	0.86	0.85	500
Weighted avg	0.88	0.86	0.85	500

The provided table furnishes a comprehensive analysis of the performance of a classification model in categorizing small metal objects into five distinct classes: Coin, Key, Nut, Screw, and Paper Clip. Each class's assessment includes metrics such as Precision, Recall, F1-score, and support. An overview of the model's overall effectiveness is presented through indicators like Accuracy, Macro average, and Weighted average.

In the "Support" column, the instance counts for each class are displayed. All five classes—Coin, Key, Nut, Screw, and Paper Clip—comprise 100 instances each, resulting in a total of 500 instances within the dataset. The "Accuracy" row signifies the proportion of correctly classified instances among the entire dataset, yielding an overall model accuracy of 86%.

The loss value of a model serves as an indicator of its performance after each optimization iteration. The assessment of the algorithm's performance employs a straightforward and accurate metric [7]. Graphs originating from diverse results based on distinct optimizers are showcased. Figure 3 portrays the accuracy and loss graph depicting the performance of the proposed model using the Adam optimizer.

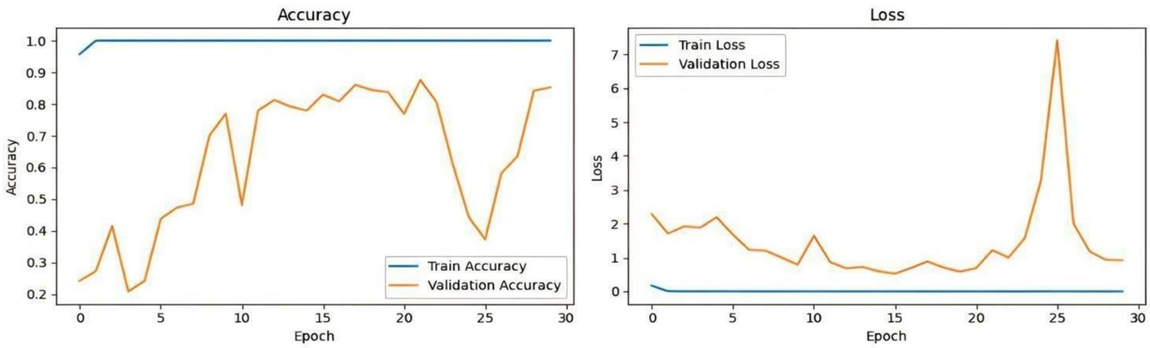

Figure 3. Accuracy and Loss Graph for Optimizer Adam

An accuracy and loss graph serves as a tracking tool for monitoring the training and validation accuracy of a machine-learning model across multiple epochs. A training accuracy of 1.0 suggests optimal performance on the training data, often associated with complex models memorizing the data or overfitting when dealing with smaller datasets. A low training loss, such as 0.1, indicates successful mitigation of prediction inaccuracies. The variability in validation accuracy throughout epochs highlights the model's generalization capacity. Early high accuracy indicates the presence of valuable training patterns. Overfitting, characterized by models memorizing training data, results in subpar performance on validation data.

The "train-validation gap" exposes the extent of overfitting, with a wider gap implying higher overfitting [11]. Validation loss is a measure of model generalization. Early low loss signifies effective pattern learning; as training advances, overfitting may occur. The fluctuations in validation loss arise due to the uncertainties in the optimization process and variations in the distribution of validation data [7].

Confusion matrices hold significant prominence in addressing classification challenges, serving as a widely used evaluation tool. It applies to both binary and multi-class classification problems. In the context of the proposed model, the confusion matrix elucidates the count of correctly classified images within the test images. Figure 4 provides insight into the confusion matrix pertaining to the Adam optimizer. Notably, the "Nut" and "Paper Clip" classes achieved 100% accuracy, while challenges persist in distinguishing between the "Key" and "Screw" classes.

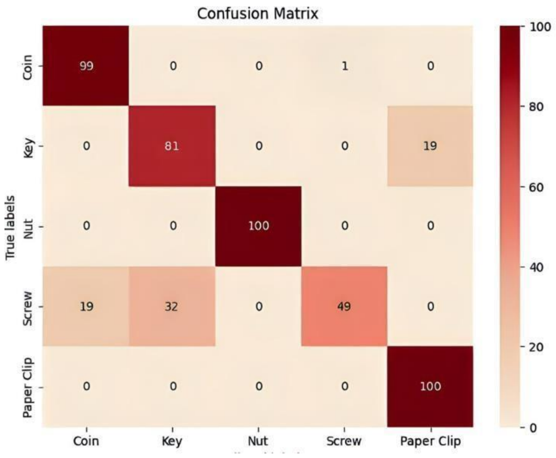

Figure 4. The confusion matrix of Adam

3.2 Result with Optimizer SGD

Table 3 provides a comprehensive overview of the executed satisfactory data, encompassing precision, recall, and F1-score for the Optimizer SGD. Each class—Coin, Key, Nut, Screw, and Paper Clip— comprises 100 instances in this scenario, resulting in a total of 500 instances within the dataset. The "Accuracy" row presents the proportion of accurately classified cases (the cumulative count of true positives and true negatives) among all instances, thus providing the overall accuracy of the model. In this instance, the model demonstrated an accuracy of 0.78, equivalent to 78%.

Table 3. Execute Satisfied Data (Precision, Recall, F1-score)

Small Metal Objects	Precision	Recall	F1-score	Support
Coin	0.84	0.99	0.91	100
Key	0.59	1.00	0.74	100
Nut	0.84	1.00	0.91	100
Screw	0.91	0.10	0.18	100
Paper Clip	1.00	0.83	0.91	100
Accuracy			0.78	500
Macro avg	0.84	0.78	0.73	500
Weighted avg	0.84	0.78	0.73	500

Figure 5 visually illustrates the progress of training accuracy, escalating from 0.2 to 0.99. This upward trajectory signifies the model's gradual improvement in classifying training data with each epoch. The concurrent ascent of validation accuracy denotes the model's successful generalization to new data. A minor dip in validation accuracy is expected as the model adapts beyond its training data. When validation and training accuracy align closely, it indicates commendable generalization, mitigating the risk of overfitting. The graph further showcases the descent of training loss, diminishing from 1.65 to 0.00. This reduction underscores the effective mitigation of prediction errors and signifies the model's better fit to the training data. Validation loss exhibits fluctuations while maintaining a downward trend, denoting the model's overarching learning process and its improved ability to generalize to novel data. Contrastingly, Figure 6 portrays the confusion matrix for the Optimizer SGD. The model exhibits strong performance in classes such as "Coin," "Key," "Nut," and "Paper Clip," boasting high precision and recall values. However, in the "Screw" class, a low F1-score suggests an area for potential enhancement. The confusion matrix serves as a valuable resource, offering insights on a per-class basis that contribute to refining the model and addressing challenges in classification tasks.

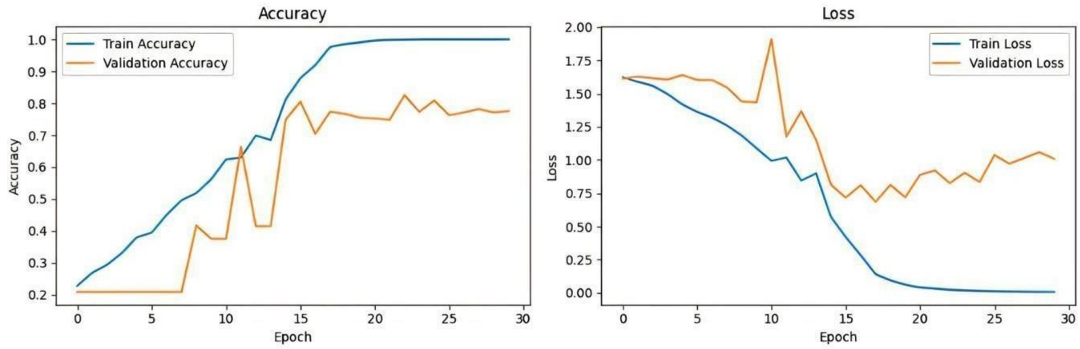

Figure 5. Accuracy and Loss Graph for Optimizer SGD

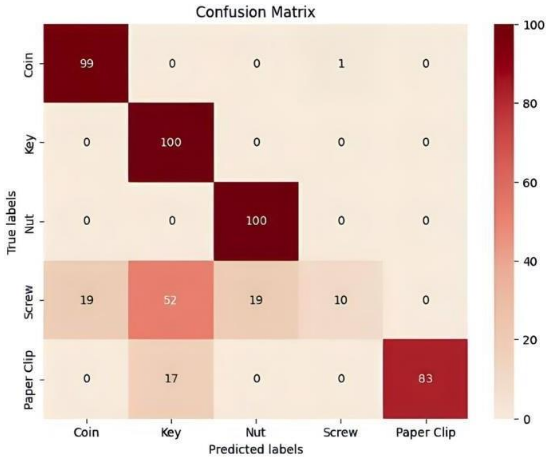

Figure 6. The Confusion matrix of SGD

3.3 Result with Optimizer RMSprop

Table 4 presents the performance metrics for the "Coin" class, demonstrating a precision of 72%, indicating 72% accurate predictions. It accomplished a 100% recall, correctly identifying all instances of the "Coin" class. Each of the classes—Coin, Key, Nut, Screw, and Paper Clip—comprised 100 instances, culminating in a total of 500 instances. The overall accuracy of the model was measured at 75%. Under the "Macro avg" category, the precision, recall, and F1-score averages were computed at 0.72, 0.75, and 0.71, respectively. The "Weighted average" takes into account metrics weighed by instance occurrences, leading to precision, recall, and F1-score values of 0.72, 0.75, and 0.71 respectively.

Table 1 Execute Satisfied Data (Precision, Recall, F1-score) for Optimizer RMSprop

Small Metal Objects	Precision	Recall	F1-score	Support
Coin	0	1.00	0.8	100
Key	0	0.80	0.6	100
Nut	1	1.00	1.0	100
Screw	0	0.10	0.1	100
Paper Clip	1	0.83	0.9	100
Accuracy			0.7	500
Macro avg	0	0.75	0.7	500
Weighted avg	0	0.75	0.7	500

Moving to Figure 7, the graph illustrates the rapid initial growth of training accuracy from 0.65 to 1.00 within the first three epochs. This indicates the model's swift learning and precise classification oftraining data. Subsequently, from epoch 3 to 30, the training accuracy maintains a consistent 1.00, reflecting consistently accurate predictions. In contrast, validation accuracy fluctuates between 0.80 and 0.75 during the course of training, suggesting less consistent generalization than observed in thetraining accuracy. Regarding training loss, there is a notable reduction from 2.00 to 0.00 within the first three epochs, highlighting effective error minimization. On the other hand, validation loss experiences a slight increase from 0.50 (epoch 0) to 0.50 (epoch 30), with oscillations indicating variability in generalization. This situation calls for caution against overfitting, potentially warranting the implementation of regularization techniques or early stopping mechanisms.

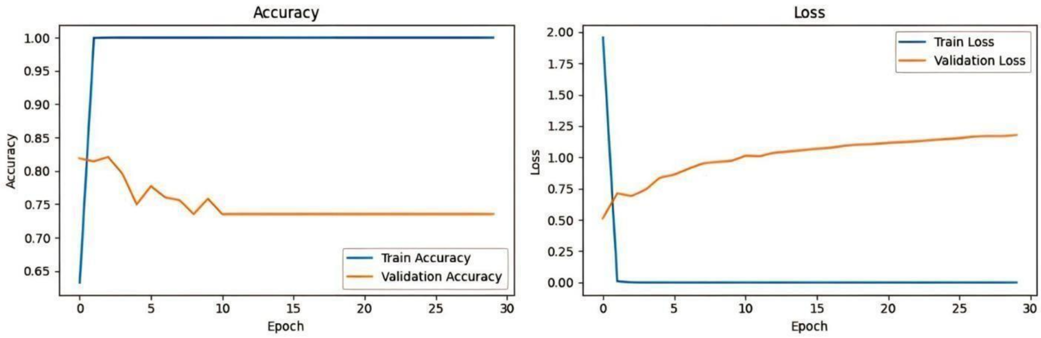

Figure 7. Accuracy and Loss Graph for Optimizer RMSprop

Figure 8 shows the confusion matrix for Optimizer RMSprop and provides insightful information aboutthe model's performance for each class, which can be utilized to improve the model or handle particularclassification task issues. The model appears to perform well in the classes "Coin," "Key," "Nut," and "Paper Clip," obtaining high precision, recall, and F1-score for those classes, according to this confusionmatrix. For class "Screw," where the F1-score is low, the model performs relatively worse, indicating an opportunity for development. As mentioned before, Optimizer Adam provides the highest accuracy result of classification. The confusion matrix illustrated how much data was correctly predicted after the classification process had been applied. The confusion matrix was one of the pieces of evidence to show the performance classification of small metal objects.

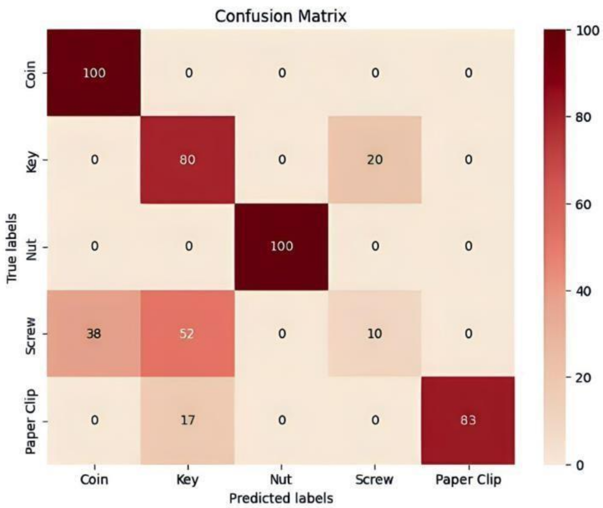

Figure 8. The Confusion matrix of Optimizer RMSprop

4. CONCLUSION

The datasets have been meticulously partitioned into three distinct, non-overlapping subsets: the training set, the validation set, and the testing set. Within this division, 70% of the data is allocated for the training set, with the remaining 30% reserved for the testing data. The training set assumes the role of training the CNN model, the validation set aids in refining hyperparameters and shaping design choices, while the testing set serves as the platform to evaluate the ultimate performance of the model. From the outcomes, it becomes evident that the Adam optimizer achieves the highest accuracy of 86%, whereas both the Adam and SGD optimizers result in slightly lower accuracies of 78% and 75% respectively. This deduction is affirmed by both the confusion matrix and the accuracy values, derived from the classification of 500 datasets through CNN utilizing diverse optimizers. The main objective of this study revolves around evaluating the efficacy of a CNN classifier technique when applied to a dataset comprising small metal objects. This small metal dataset necessitates meticulous scrutiny and preprocessing, including cropping, which ultimately contributes to heightened accuracy compared to unprocessed classification. Image resizing is necessitated by factors such as memory constraints, the lack of inherent improvement in CNN performance with larger images, potential reduction in batch sizes leading to prolonged training times, and the necessity to align image dimensions with classifier specifications, particularly when employing pre-trained models. In this investigation, Convolutional Neural Networks (CNNs) were chosen as the classifier model. Among the multitude of CNN variants, the ResNet-50 model was specifically selected to enhance the classification outcomes. The architecture of the CNN plays a pivotal role in training datasets encompassing diverse models, essentially influencing the accuracy of the output. The utilization of the confusion matrix, which effectively quantifies the number of datasets that were inaccurately predicted, stands as an optimal choice for analysis, offering insights into the classification results and serving as a direct indicator of the model's accuracy. The conclusions derived from this study underscore the pivotal role of data volume in achieving classifications characterized by high accuracy.

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