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THE ENSEMBLE METHOD AND SCHEDULED LEARNING RATE TO IMPROVE ACCURACY IN CNN USING SGD OPTIMIZER

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Abstract

Indonesia is an agricultural country where most people work as farmers. As an agricultural country, Indonesia produces staple foods, such as rice, corn, sago, and fruits. This research uses the Convolutional Neural Network (CNN), one of the popular algorithms in Deep Learning to classify two varieties of fruit using Stochastic Gradient Descent (SGD) optimizer. The data used in this research is the primary data collected using a smartphone camera. The data are 400 images of two fruit varieties, Mango, and Avocado. The main research objective is to obtain the highest accuracy by modifying the classifier model and learning rate. The model modification, this research uses an ensemble system while in learning rate using an exponential scheduled learning rate. The result shows that the accuracy of the ensemble system is 0.99, the scheduled learning rate is 0.97, while without modifications is 0.53, respectively. However, when using the SGD optimizer to train CNN, it is advised to use a predefined learning rate. A shorter training period with sufficient model accuracy and practicality supports the scheduled learning rate.

Keywords: CNN, Ensemble, Learning rate, SGD.

1. Introduction

Indonesia is a tropical country with two seasons with a diversity of flora and fauna. The number of floras in Indonesia is approximately 30.000, but only about 4.000 varieties have been used by humans [1]. Indonesia is indeed known as a country with a high genetic diversity of tropical fruits [2]. In addition to being a supplementary food, some fruits have medicinal properties, although the public is not sure about their specific benefits. This phenomenon is like the case of fruit preservation, where the public acknowledges the importance of preserving these fruits but may need to learn how to sustain their presence in the future [3].

Each fruit has characteristics in which its shape and colour can be distinguished. Some fruits have similar shapes and colours, so many people find it difficult to identify the varieties of fruits. On the other hand, due to the many different fruit kinds of resemblances in shape, colour, and texture, classifying fruit varieties using computer vision is still challenging [4]. Apple is one of the fruits that has many varieties, such as the Malang Apple, Fuji Apple, and Envy Apple [5]. Those apple varieties have similar shapes and colours and tend to make people need to distinguish it. However, the use of artificial intelligence and image processing to produce computer-based fruit variety detecting systems has become possible.

The objective of image processing is to maintain uniformity in the image properties of the model dataset when applied to multiple images [6]. One of the algorithms often used is called Convolutional Neural Network (CNN). Since 2012, Convolutional Neural Networks (CNNs) have been successfully applied in computer vision and have significantly outperformed most handcrafted image features [7]. In addition, the CNN algorithm enables images to compute and find useful information that humans need.

However, this experiment in fruit classification based on shape and colour is just a test. This study is more concerned with altering the model's performance by utilizing an ensemble system and an exponential scheduled learning rate. The optimizer used in the research is SGD, which has been shown in several studies to have a low level of performance. This phenomenon is a challenge for researchers to improve model performance using the SGD optimizer.

2. Related Work

Previously, several researchers did their research on fruit classifications which focused on data preparation, image degradation, algorithms, and others. The objectives of their research were related to the improvement of the accuracy of the model. Therefore, the model could classify the new objects accurately.

A study on image classification was conducted to determine the effect of image quality on model’s accuracy. This study concluded that poor image quality causes the model accuracy decrease significantly. These findings confirm that image pre-processing is a fundamental and mandatory process to improve image quality [8]. A less sharp image does not necessarily cause poor image quality, but it can be due to the focus of the objects to be observed. Images with complex backgrounds, like those of natural settings, frequently exhibit this. If it is mishandled, images like the one in this situation will reduce the value of model’s accuracy. Therefore, a machine learning can only create accurate predictions if the model accuracy is high [9].

A study focused on the classification of local fruits was undertaken to aid in identifying indigenous fruit varieties. This investigation was carried out in Bangladesh and involved utilising eight distinct fruit types, amounting to a dataset of 3,240 instances. Deep learning techniques were employed to categorise these local fruits. To enhance accessibility for supermarket patrons seeking information about local fruit varieties, a web-based detection system was developed. Multiple architectural models, including ResNet-50, VGG-19, Inception-V3, and MobileNet, were employed in this study to extract the most informative features. Notably, MobileNet outperformed the others, achieving an accuracy rate of 99.21% in this research [10].

Fatigue can occasionally cause weakening in human vision. This condition could be better news since papaya fruit must be packaged according to its level of ripeness. A study was proposed to categorize the three stages of papaya fruit maturity. In this study, 300 samples in three maturational levels were employed. Local binary pattern (LBP), histogram of oriented gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), K-nearest neighbour (KNN), support vector machine (SVM), and Naive Bayes are the features and classifiers used in machine learning methodologies, respectively. Seven pre-trained models, including ResNet101, ResNet50, ResNet18, VGG19, VGG16, GoogleNet, and AlexNet, are included in the transfer learning approach. This study indicated that VGG16 had the highest accuracy compared to the other models [11].

The study proposes a system that estimates the type, maturity level, and weight of date fruits, utilizing deep learning and computer vision techniques. The suggested method applies four pre-trained models on the date fruit picture dataset: ResNet, VGG-19, Inception-v3, and NASNet. The system employs ResNet for DMES and DTES and SVM for DWES. The system exhibited good recall, precision, accuracy, and F1 score, outperforming other designs in the same area. The findings demonstrate that both DMES and DTES performance measures were met with exceptional success by the ResNet model included in the suggested solution [12].

Regarding to the optimizer frequently used for image classification, ADAM is known as an optimizer that improves SGD and RMSProp. SGD, however, is a straightforward optimizer with a fast-processing rate, but less accurate. This problem investigation will be done using the research question of how to improve the model's accuracy using SGD optimizer.

Prior research endeavours have explored numerous strategies to enhance model accuracy. Among these strategies is selecting the most suitable optimizer to maximize accuracy improvement. In a study to facilitate fabric recognition for the visually impaired, six optimizers were systematically compared to identify the most effective one. The six optimizers encompassed Stochastic Gradient Descent, Root Mean Square Propagation, Adaptive Moment Estimation, Adaptive Delta, Adaptive Norm, and Adaptive Gradient. Each optimizer was trained using three distinct learning rates (1E-3, 1E-4, and 1E-5). Of the six optimizers evaluated, ADAMAX demonstrated the highest accuracy, achieving an accuracy rate of 92.91%, while SGD lagged with an accuracy of just 68.91%. Consequently, the relatively lower performance of SGD has rendered it less favoured than other optimizer choices, even though it may still benefit from alternative improvement methods [13]. Prior investigations have indicated that the SGD Optimizer yielded unsatisfactory outcomes across all four models. Consequently, it is advisable to consider alternative optimization algorithms for supervised deep learning models, as SGD proved to be the less favourable choice [14].

Additional research on CNN and its enhancements was undertaken in traffic sign recognition. A novel approach was devised, combining a hybrid technique, and stacking ensemble methods to optimize model performance. As presented in this study, the utilization of a stacking ensemble model leveraged the amalgamation of pre-trained subnets to yield superior results. Notably, both model parameters and hyperparameters remained consistent, with the only variation being the input images. Notably, all layers within the sub-models were configured as non-trainable to safeguard the parameter values within the existing sub-models.

The proposed method, entailing a hybrid image enhancement approach and CNN stacking ensemble, yielded remarkable results, achieving a test accuracy rate of 99.75% on the German Traffic Sign Recognition Benchmark (GTSRB) dataset. This notably surpassed the accuracy attained in previous studies in the field, which recorded accuracy rates of 98.8% and 99.46%. Additionally, this research unveiled the substantial impact of data augmentation in enhancing accuracy [15].

Additionally, a study delved into ensemble techniques to develop a Hyperspectral Image (HSI) classification system, utilising a transfer learning foundation. The system additionally integrates an enhanced label smoothing method to enhance the precision of classification. This research introduces a more efficient and precise approach to HSI classification, offering potential advantages in diverse applications like remote sensing, environmental monitoring, and mineral exploration. While specific accuracy figures from the research are not disclosed, it is noted that the CNN ensemble exhibits commendable classification performance in comparison to state-of-the-art methods [16, 17].

In pursuing enhancing model accuracy within CNNs, the significance of the learning rate in this endeavour cannot be understated. Research on optimizing learning rates has demonstrated a substantial enhancement in model accuracy. A methodology known as Switching from Constant to Step Decay (SCTSD) has been introduced to elevate model performance, particularly regarding accuracy. The outcomes of experiments affirm that SCTSD outperforms alternative scheduling techniques across diverse datasets [18]. Several research regarding with improvement in learning rate also was done in previous research [19-21].

The research results regarding improving model performance in studies that have been carried out using ensemble techniques and learning rate settings are the basis for this research. It is proven that the ensemble and learning rate approaches have the opportunity to be developed to increase accuracy. The different thing done in this research was to compare the training effectiveness without ignoring the accuracy results obtained by each approach.

3. Method and Theoretical Background

In the present research, the fruit varieties classification was done using Convolution Neural Network (CNN) to classify two varieties of fruit. The classification of fruit varieties is essential in computer research and industrial applications [4]. The various of CNN components [22] are shown in Fig. 1.

The images will be classified into the CNN model using the convolution layer to extract the various features. The results of the convolution process are forwarded to the next layer, i.e., the pooling layer. The objectives of the pooling layers are to reduce the computational process and to make a bridge between convolutional and fully connected layers, which were placed before the output layers. In the fully connected layers, the images are flattened and forwarded to it.

Fig. 1. CNN's various components.

In machine learning, the learning rate is one of the most critical factors. The learning rate controls how rapidly or slowly the network model modifies its weights based on the gradient of the loss function throughout the training process. The model will not converge properly if the learning rate is too high, while if it is too low, the training process will proceed very slowly. Unscheduled and scheduled settings exist for the learning rate. There are positives and negatives to any environment. Scheduled learning involves more complex settings but has more benefits than unscheduled learning. By this definition, choosing the proper learning rate will affect the model's accuracy [23].

An ensemble method in CNNs is a strategy that entails training and mixing various convolutional neural network models to boost the model's performance. Different ensemble algorithms have different methods for choosing the trained baseline classifiers. Based on whether they are homogenous or heterogeneous, two ways produce variety among the basic classifiers. A homogenous ensemble comprises baseline classifiers of the same kind, each built on distinct data sets. Different numbers of baseline classifiers constitute a heterogeneous ensemble because they all use the same set of data. In this study, the heterogeneous strategy was suggested [24]. The general structure of the ensemble system is shown in Fig. 2 [25].

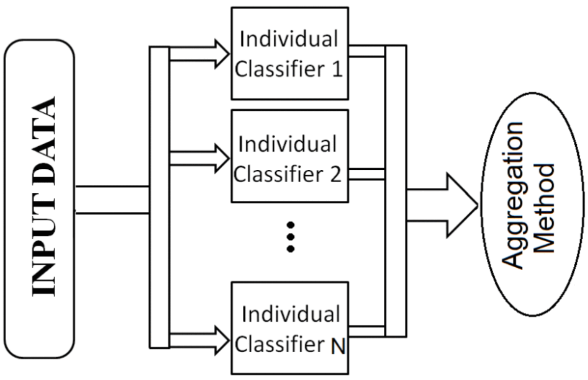

Fig. 2. The general structure of ensemble system.

The data used in this research is primary data, which has more value than secondary data in achieving the research objectives. Data were collected by photographing two varieties of fruit using a smartphone camera. The number of images on each fruit is 200, so the total data set used in this research is 400. The process of taking images was done on February 17, 2023, in Yogyakarta, Indonesia. The example of the data set in this research is shown in Fig. 3.

Fig. 3. The example of data sets.

Following the classification approach, the data set was divided into two parts with a ratio of 75%:25%, with 75% used for training and 25% for validating data. A confusion matrix was used to assess the model's accuracy, precision, recall, and F1 score. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four variables that were utilized to calculate the model performance. The formulas for calculating Accuracy, Precision, Recall, and F1 are shown in Eq. 1-4, respectively [26, 27].

$$Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + TN + FP + FN}} \quad (1)$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP + FP}} \quad (2)$$

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP + FN}} \quad (3)$$

$$F1\ Score = \frac{\mathrm{2(Precision\ x\ Recall)}}{\mathrm{Precision + Recall}} \quad (4)$$

The data set, however, is ideal for achieving the goals of the study. To fulfil the goals of the research, editing should be done. For example, to create a facial recognition application, the researcher needs multiple photos of people in a complicated context. To identify the target object in this instance, the backgrounds need to be cleared. Pre-processing techniques are crucial for minimizing or eliminating disruptions during image acquisition and subsequent analysis [28], is a multi-step procedure that tries to extract features by eliminating noise [29]. Figure 4 outlines the process for obtaining image features.

Adjusting an image's size and quality, or reducing noise is done for image classification by using pre-processing steps. On the other hand, feature mining aims at automatically extracting critical information from the image [30], while featuring selection is used to find the intrinsic bands' information [31].

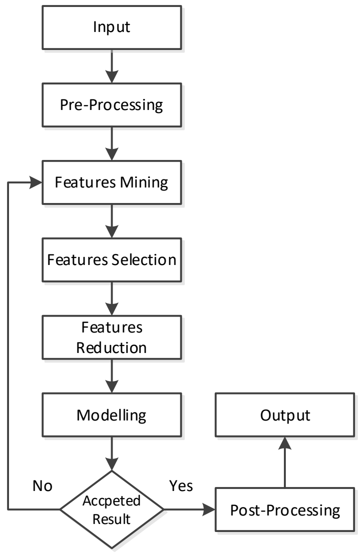

Fig. 4. The step of image processing.

The next step in image processing is modelling, which aims at developing a model to classify new objects and finding the model's accuracy using a confusion matrix. When the model's accuracy was low, the researcher had to increase it because it can cause inaccurate predictions.

4. Results and Discussion

Ensemble methods involve the fusion of multiple CNN models to boost overall predictive performance. They are frequently utilized to increase the precision and resilience of classification tasks [32-34]. Ensemble methods are beneficial as they have the potential to mitigate overfitting, enhance classification precision, and enhance a model's resilience to data noise or fluctuations. In this study, the chosen ensemble method is Voting Ensembles [35]. In this voting-based approach, CNN models are trained on the same dataset [36]. Every CNN model produces an output during the prediction process, and the final prediction is established through a majority vote. The utilization of the voting methodology is justified by its effectiveness and has been proposed to enhance algorithmic accuracy [37].

Ensemble voting involves several steps: (1) Training multiple CNN models, (2) Producing predictions, (3) Conducting a vote, (4) Combining predictions, and (5) Arriving at the final prediction. This study employed five models, each trained for 15 epochs, utilizing a learning rate 0.001. The research focuses on a binary classification task involving two types of fruits, hence the use of "binary_crossentropy," a commonly employed function for binary classification, often referred to as log loss or logistic loss [38]. Binary cross-entropy is commonly preferred because it incentivizes the model to generate probability-based outputs that can be seen as confidence levels. This function finds widespread application in logistic regression and neural networks, particularly in tasks like spam detection, sentiment analysis, and medical diagnosis, where the objective is to categorize data into one of two distinct classes. After the training process, the results are shown in Fig. 5.

Based on the data in Fig. 5, it is known that the training accuracy value is 0.97, while the validation accuracy value is 0.99. This data shows that training and validation accuracy is in the high category. These results also indicate that the model can learn effectively and will be able to make accurate predictions. A training accuracy of 0.97 and a validation accuracy of 0.99 strongly suggest that the model performs exceptionally well. Validation accuracy is also shown in the confusion matrix in Fig. 6.

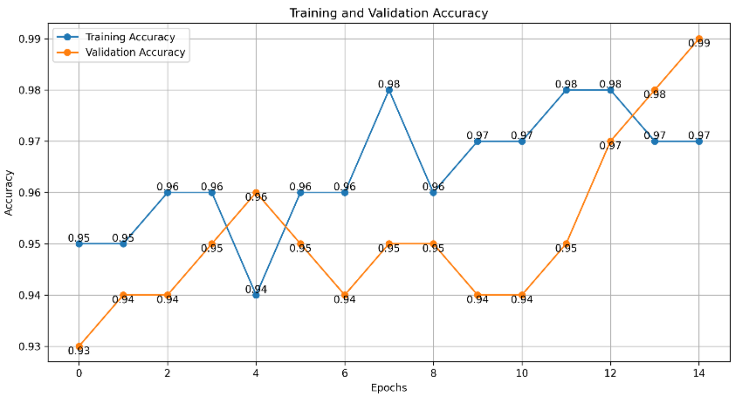

Fig. 5. The results of training and validation accuracy using ensemble method.

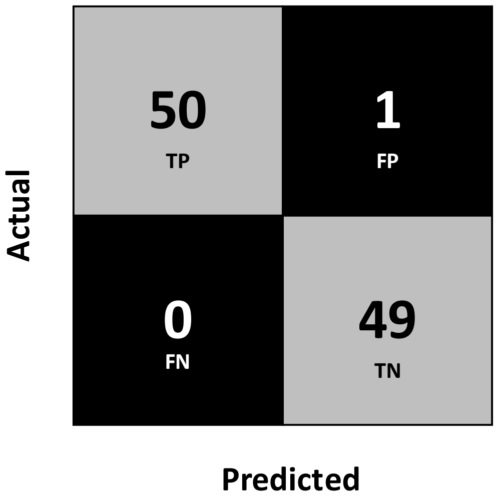

Fig. 6. Confusion matrix of ensemble method.

In the true positive (TP) area of the confusion matrix, the data display a value of 50, indicating that the model correctly predicted 50 positive data points, and those actual data points are positive. A false positive (FP) value of 1 on the other hand means that although the model predicted a positive value, the actual value was negative. A true negative (TN) count of 49 signifies that 49 instances were correctly predicted as negative when they were indeed negative. Ideally, positive, and negative data distribution should be balanced, with both categories having 50 instances each. The accuracy value can be determined using the confusion matrix formula: ((50+49)/100) = 0.99. Additionally, values for precision, sensitivity, and specificity can be determined. The model's sensitivity is its capacity to forecast positive situations, and the precision value is used to assess meaningful occurrences from the samples taken. The capacity of the model to identify negative cases is specificity, which is the reverse of sensitivity. Precision is calculated with (50/(50+1)), which results in a value of 0.98, while specificity is calculated with (49/(49+1)), which results in a value of 1. Sensitivity is calculated with (50/(50+0)), which results in a value of 1.

The next step is to calculate the specificity and sensitivity of the Area Under the Curve (AUC), which compares various classifiers by calculating the Area created by the ROC curve. The ROC curve shows specificity on the X-axis and sensitivity on the Y-axis. A model with an AUC value close to (0.1) is an excellent classifier model. The value of AUC is 0.49 when calculated using ((1*0.98)/2). This classifier model's AUC value, which is close to 0.1, demonstrates its high quality.

The model accuracy results obtained using the ensemble method were then compared with the scheduled learning rate method. Modifications to the learning rate also play a role in increasing model accuracy. The learning scheduling system used in this research is exponentially based, so the learning rate can be reduced as the epochs progress. The reason for using this method is that it consistently reduces the learning rate and can prevent overfitting. The results of the training process carried out are shown in Fig. 7.

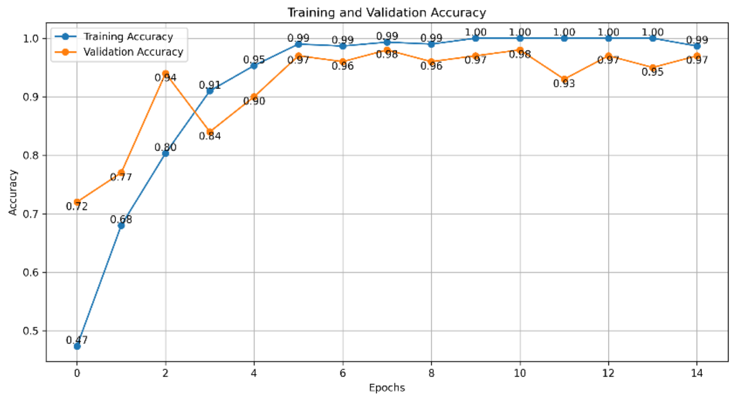

Fig. 7. The results of training and validation accuracy using scheduled learning rate.

Based on Fig. 7. The accuracy and validation value of the model is 0.97. Even though the value is in the high category, the value is still lower compared with the ensemble method. These results were then validated using the confusion matrix shown in Fig. 8.

Compared to the ensemble method's confusion matrix, the scheduled learning rate exhibits variations in the false negative (FN) and true negative (TN) categories. True negatives have a count of 48, while false negatives stand at 2. This data indicates that 48 instances were correctly predicted as negative and were indeed negative, but 2 cases predicted as negative turned out to be positive. In the positive segment (TP and FP), the results mirror the ensemble method's results, with 49 correctly predicted positives and 1 instance incorrectly predicted as positive when negative. This discrepancy in outcomes results in differences in accuracy compared to the ensemble method.

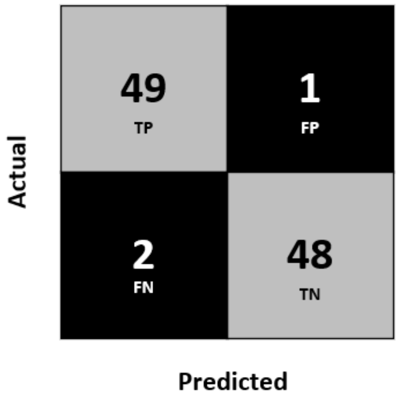

Fig. 8. Confusion matrix of scheduled learning rate method.

In the scheduled learning rate approach, the sensitivity is computed as (49/(49+2)), resulting in a value of 0.96, while the specificity is calculated as (48/(48+1)), yielding a value of 0.98. By utilizing these sensitivity and specificity values, we can determine the AUC (Area Under the Curve) as ((0.96 * 0.98) / 2), which equals 0.47. Regarding the ROC (Receiver Operating Characteristic) curve analysis, the AUC value obtained through the scheduled learning rate method is closer to 0.10 than that of the ensemble method.

In comparison to training trials without changes to either modelling or learning rate, the outcomes of the improvised methods utilized with the SGD optimizer were significantly better. Testing without change only resulted in training and validation accuracy of 0.50 and 0.53, respectively. This outcome differs significantly from modification trials' ensemble and learning rate outcomes. In Fig. 9, the test results are displayed without change.

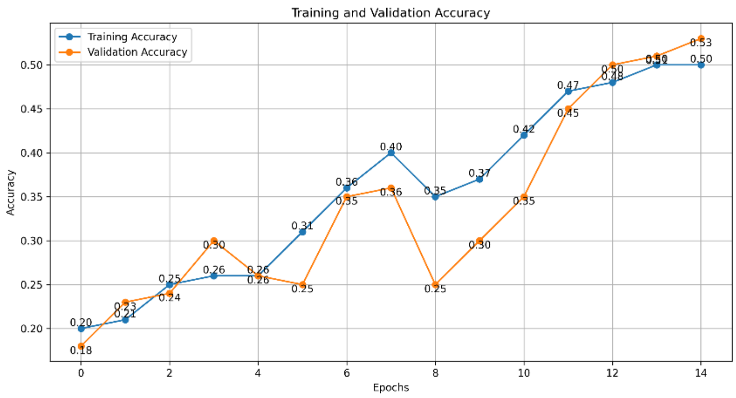

Fig. 9. The result of training using SGD optimizer without modifications.

According to the findings of two experiments conducted for this study, changes to the model and learning parameters have a considerable impact on model correctness. These two approaches must be used in a way that best suits the situation because they play distinct roles in the scenarios in which they have been used. The required training time and hardware resources must also be considered, so the highest accuracy cannot be utilized as the primary criterion for selecting this method.

Even though both methods produce highly high results and the difference between them, as measured by accuracy value, could be more substantial, each technique serves a unique function. The ensemble technique combines predictions from multiple models into a more accurate forecast to improve model accuracy. This Ensemble method's benefits include preventing overfitting and improving model accuracy [39]. The ensemble method's capacity to identify various patterns and features in the data is an intriguing aspect [40].

In contrast to the ensemble method, the planned learning rate seeks to alter the learning rate while training. Overcoming over fitness and reducing training time are two objectives. In order to optimize training, a scheduled learning rate is frequently employed with CNNs. The learning rate setting has the exciting advantage of being more realistic and capable of speedy problem-solving. However, determining the learning rate necessitates experimentation and comprehension of the situations that must be handled.

Therefore, the suggested strategy in this study is to adjust the learning rate to enhance CNN model accuracy despite being 0.02 lower compared to the ensemble method. This recommendation is based on two key factors: (1) the significant difference in training speed, although still a matter of minutes due to the relatively small dataset, and (2) the attained accuracy is adequate for making predictions. These considerations form the basis for advocating the learning rate adjustment approach during CNN training.

Even though the accuracy achieved is sufficient, this research has room for improvement. The primary limitation primarily stems from the limited dataset of only 400 samples. A larger dataset, preferably containing thousands of samples, should be used to validate the conducted experiments further. Additionally, exploring other ensemble techniques, such as ensemble voting, and refining learning rate settings, such as adopting performance-based decay, should be considered.

5. Conclusion

It was determined from the experimental findings and study discussion that the validation accuracy values for the ensemble method, scheduled learning rate, and without modification were 0.99, 0.97, and 0.53, respectively. The ensemble technique is the best and, without modification, is the worst, as measured by the model accuracy value. However, a scheduled learning rate is suggested when utilizing the SGD optimizer to train CNN. The scheduled learning rate is supported by practicality and a shorter training period with enough model fidelity. This research must be expanded with more ensemble types and learning rate types to fully comprehend the kind of improvisation that most effectively meets the study. Extra data is also required for training and validation to make the model more accurate in predicting new items.

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