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Classification of Brain Tumors by Using a Hybrid CNN-SVM Model

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ABSTRACT

Brain tumors are diseases that involve the growth of brain cells, causing abnormalities in the brain region. An MRI scan is a useful tool for tumor detection. Researchers can process the obtained image data to conduct research capable of detecting brain tumor disease. Classifying brain tumors facilitates effort, planning, and accurate diagnosis, enabling the formulation and evaluation of treatment options for a patient with a brain tumor. The research was conducted to classify whether or not there was a tumor in the brain by using a combination of algorithms, namely CNN, to extract features from image data and then use SVM as a classification. CNN is a popular algorithm that deals very effectively with the complexity and variation of image data, whereas SVM is an algorithm for classification that maximizes margins and generalizations to produce accurate classifications. The project's goal is to create a hybrid model that can classify two labels based on image preprocessing processes, feature extraction, and brain tumor image data classification. In this study, the results of the CNN-SVM hybrid were able to obtain the highest score with Adam optimization and learning rate 0.001, accuracy of 98.92%, precision 98.92%, recall 98.92%, and f1-score 98.92%.

I. Introduction

The human brain's nervous system is one of the most complex biological systems. The brain has a volume of about 1350cc and consists of one hundred billion neurons, or supporting nerve cells, that are connected to the spinal cord[1]. The brain, along with the spinal cord and nerves, functions as the command center of the human nervous system. The brain consists of three main parts: the cerebellum, the brain stem, and the cerebrum. One of the ways the brain controls most body activities is by processing, integrating, and regulating the information it receives from the sensory organs[2]. Brain health is when the brain functions well in terms of cognitive, sensory, behavioral, and motor aspects. Physical health, environment, safety, and security are some of the factors that can influence how the human brain develops[3]. If not cared properly, many disorders and diseases can endanger brain health.

A brain tumor disease refers to when there is abnormal and uncontrolled cell growth within or around the brain. Brain tumors are one of the most malignant tumors that can happen in humans after blood tumors (leukemia)[2]. Brain tumors can be classified as primary when abnormal changes occur in the brain cells themselves. On the other hand, secondary or metastatic brain tumors originate from tumor cells in other parts of the body that subsequently spread to the brain[4],[5]. If not treated promptly, tumors can lead to severe and dangerous brain dysfunction that can potentially endanger life. As a result, significant efforts have been made to identify brain tumors early using digital equipment, one of which is through anatomical imaging approaches. For examples, by using CT scans, X-rays, and Magnetic Resonance Imaging (MRI)[4],[6]. After the patient undergoes an examination, a radiology specialist will analyze the images produced by the MRI machine and make decisions based on them. Doctors can use brain image segmentation to plan treatments and evaluate the actions needed to address the patient's brain tumor. Due to the complexity of MRI images, brain image segmentation remains a significant challenge for the medical community[7]. Consequently, additional solutions can be implemented through image data processing to assist doctors in early detection of brain tumors. One method for classifying brain tumor images is Convolutional Neural Network (CNN), which can aid doctors in diagnosing the patient's condition[8].

The Convolutional Neural Network (CNN) technique is one of many approaches that can be used for the classification process. Pattern recognition in images using deep learning with CNN is very popular[9]. This method can easily differentiate images with similar and hard-to-recognize attributes. For large-scale image classification, CNN is good at automatically and efficiently extracting complex features.

In previous studies, CNN methods have been used to classify brain tumor diseases. Research by Monikka et al. (2022) focused on classifying four types of brain tumors using 3167 brain tumor images. They employed the MobileNet V2 architecture with transfer learning techniques that achieved an accuracy of 88.64%[10].

April et al. (2024) conducted brain tumor classification using a hybrid approach of CNN-ViT. They combined deep learning algorithms where CNN and ViT are used to extract feature vectors that are then merged before classification. This research explored four optimization scenarios. The combined algorithm with its optimized scenarios achieved a highest accuracy of 94% using Adam optimization and a learning rate (parameter) of 0.001%[11].

Radical et al. (2021) conducted brain classification using a hybrid CNN-ELM approach. They utilized CNN for feature extraction, followed by integrating the output into ELM. The study explored three scenarios varying the number of nodes in the hidden layer and filters in the convolutional layer. The proposed model achieved a highest accuracy of 91.4% with precision, recall, and F1-score values at 91.5%[12].

Kartika et al. (2023) conducted classification of brain tumor diseases using MRI data from both tumor and healthy brains. The study proposed a system aimed at automatically detecting brain tumors to potentially reduce diagnosis costs. Their method involved using GLCM features for feature extraction, combined with the K-NN classification method. The system tested 1150 images and achieved a best accuracy of 81% with the optimal value of k set to 3[13].

There is related research using the hybrid CNN-SVM method for classifying skin diseases. In this study, 300 images per type were used, with 240 images for training and 60 for testing, employing two scenarios in the preprocessing stage. The research utilized CNN for feature extraction and linear and RBF kernels for SVM classification. The proposed method achieved a best result of 65.33% accuracy.[14]

Based on the explanation provided above, this research aims to develop an approach that can be utilized effectively. The study will focus on feature extraction from brain tumor MRI images using Convolutional Neural Network (CNN) and Support Vector Machine (SVM) for final classification processes with data of different classes.

This paper is structured as follows: Part I begins with an overview of the research rationale. Part II discusses the materials and proposed models for the study. Part III explains the experimental results and their discussion. Finally, Part IV concludes with a summary of the research findings.

II. METHOD

The main explanation of this study is the classification of brain tumor diseases. There are several stages to be done in this research to support its success and prevent errors in the process. The flow in the study is shown in Figure 1.

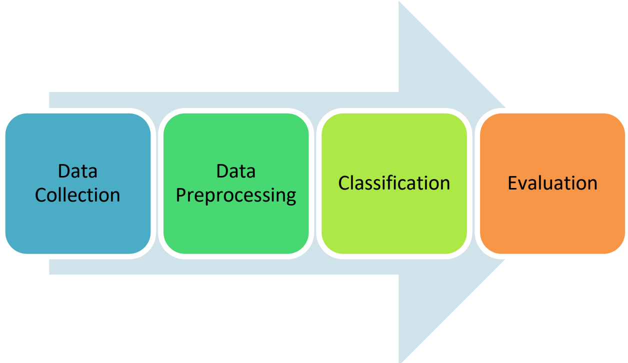
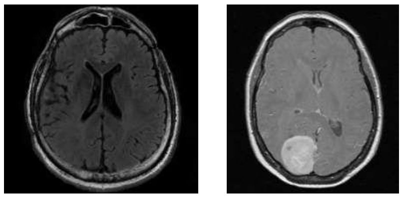


Figure 1. Research Stage

A. Data Collection

In this study, the first process is the collection of image data to be done. The data set used is a data set of brain tumor MRI images. The dataset used is downloaded from Kaggle.com (https://www.kaggle.com/datasets/luluw8071/brain-tumor-mri-datasets). The tumor data set contains MRI data of 8764 images with two classes of brain images of diagnosed tumors (5178) and not diagnosed tumors (3586) brain images. The sample image can be seen in Figure 2.



Not Diagnosed Diagnosed

Figure 2 Sample Image Brain Tumor

B. Data Preprocessing

Preprocessing data is crucial to prepare data before using it for machine learning. At the preprocessing stage this is divided into several stages as follows; after the data is entered the data will be resized with the size of the digital image changed to 64pixel x 64pixels. The data will be gathered into one according to the division of training data and testing data by 80:20. Label encoding is a method used for labeling. Data normalization is a database design logic method that combines relational features to create a well-structured relational structure without redundancy. In other words, the goal of data normalization is to transform data into values ranging from 0 to 1, enabling calculations with the data without generating excessively large numbers. This ensures that the data is ready for training and testing the model effectively. Once the preprocessing stage is complete, the data is ready for use in machine learning models to make accurate predictions[6].

C. Classification

The classification stage involves designing the model used in this study, which is CNN-SVM. This means combining both models: CNN for extracting features from brain tumor images using optimized parameters and learning rates to achieve the best accuracy, followed by SVM for the classification process.

1) Convolution Neural Network (CNN): Convolutional Neural Network (CNN), one type of deep learning algorithm. CNN uses the evolutionary concept of MultiLayer Perceptron (MLP) designed to process data generally in two-dimensional shapes[15]. CNN, can identify any aspect of the received image due to its complex structure. The application of CNN is common in image analysis. Several major layers consist of the CNN: the convoluted layer, the pooling layer, and the flatten[16]. The process of convolution operation involves applying a mathematical matrix over each pixel of the image, shifted across the image using a kernel. Pooling is performed after convolution to reduce the dimensions of the image and enhance its robustness against scale and orientation changes. The flatten layer transforms the structured feature maps into a single vector from a multidimensional array, which serves as input for the layers that are fully connected. In final step, these layers categorize the processed image output from neurons in the preceding layers[14].

2) Support Vector Machine (SVM): Support Vector Machine (SVM), refers to a regulated machine learning model which applies learning algorithms in the classification process and regression analysis. SVM uses a set of mathematical functions known as kernels as input data[17]. It is often used to classify data that can be separated linearly. For data that cannot be separated linearly, kernel functions are applied to map the input data to feature space[18]. Both linear and non-linear SVMs can handle regression and classification problems. The SVM algorithm finds the best hyperplane to classify data, which separates all data points from one or several classes[19]. The boundary that separates two groups of data in a graph is called a hyperplane. In the SVM algorithm, a data object with the outermost position of its cluster that is closest to the hyperplane can be said to be a support vector[15]. SVM addresses problems by finding the minimum distance between the decision boundary and each sample. To find and create a hyperplane, SVM determines the hyperplane margin from the closest distance between data points of two different classes.

3) CNN-SVM Model: model combines two machine learning algorithms by modifying the output layer of the CNN model to use SVM classification [14]. These algorithms are integrated to create a hybrid model for the study. CNN is a very effective algorithm that handles the complexity and variation of image data well, whereas SVM is an algorithm for classification that maximizing margin and generalization to produce accurate classifications. In the feature extraction fitur, the CNN algorithm is utilized. The feature vectors it produces are then employed in the classification process using the SVM algorithm. The following is how the CNN-SVM hybrid model operates: the model functions by first taking input images that are normalized and centered through the input layer, then, training process is used to train the original CNN with output layers. Using a linear kernel, SVM replaces the output layer and utilizes the results from hidden layers as additional feature vectors during training. New decisions for testing images via feature extraction will be made after the SVM classifier has trained data.[20].

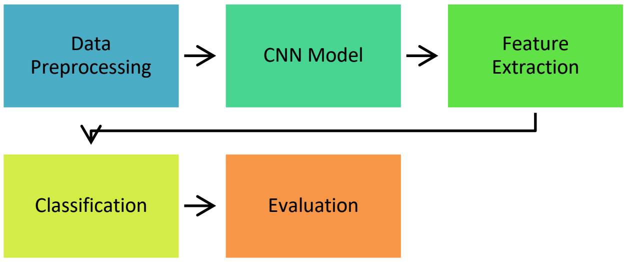


Figure 3. CNN-SVM Model Planning Stream

As depicted in Figure 3, the process of the hybrid CNN-SVM model begins by feeding data from the preprocessing stage into the CNN. The CNN architecture generates feature vectors, which are then passed to the classification layer using the SVM method. This produces performance metrics and accuracy values, that are then evaluated.

D. Model Evaluation

One way to evaluate the performance of a classification method is to use a confusion matrix, which basically contains information that compares the system classification results with the classification to be done.

TABLE 1
CONFUSION MATRIX

Actual Value	Positive Prediction	Negative Prediction
Positive (1)	*True Positive (TP)*	*False Negative (FN)*
Negative (0)	*False Positive (FP)*	*True Negative (TN)*

Through the calculations done using the confusion matrix, we can see how well the machine learning model is used. Measures performance through accuracy calculations, often used evaluation values based on the following formula:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

Accuracy is an evaluation of how close the prediction is to the true value. That is, accuracy measures the overall proportion of the true prediction, including the positive and the negative[21].

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

Precision is an evaluation method that compares the amount of information that is relevant to the quantity of information selected by the system, whether relevant or irrelevant[21].

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

Recall is an evaluation method that compares the amount of relevant information successfully detected by the system with the actual amount of the relevant information in the data set, including those that were successfully found or not.[21].

$$F1 - Score = \frac{2\ x\ presisi\ x\ recall}{presisi + recall} \quad (4)$$

F1-Score is an evaluation that calculates the weighting averages of precision and recall. Values vary between 0 and 1; the higher the F1-score values, the better the accuracy and recalls of the classification model[21].

E. Scenario

A research scenario is a plan used by researchers to collect data, analyze data, and draw conclusions based on research findings. This study involves the execution of four distinct scenarios. The research scenarios are created to be able to compare the evaluation results of the model using optimization and learning rate. Here's the scenario for the research.

TABLE 2
RESEARCH SCENARIO

No.	Model	Optimization	Learning Rate
1.	CNN-SVM	Adam	0,001
2.			0,0001
3.		RMSProp	0,001
4.			0,0001

III. RESULTS AND DISCUSSION

A. Data Collection

In this study, the data used is obtained from Kaggle.com. The dataset consists of two classes: brain images diagnosed with tumors and brain images without tumors. There are 8,764 images in the dataset, with 3,586 images representing non-tumor brain data and 5,178 images of tumor-diagnosed brain data.

B. Data Preprocessing

In the data preprocessing stage, the collected data undergo several steps. At this stage there are several steps taken such as rescale image changes the size of the data to 64x64 pixels, the data used is divided into two: data training (7012) and data testing (1752), then encoder labelling techniques performed to do labelling, and data normalization ensures that the pixel values of the image are in a smaller and more uniform range.

C. Classification

The hybrid CNN-SVM model is employed for the brain tumor classification stage. The CNN model utilizes parameters such as Adam and RMSProp optimization, with learning rates set at 0.001 and 0.0001. The SVM model uses a linear kernel for classification purposes.

For the accuracy results obtained from tests comparing the pure CNN with the CNN-SVM hybrid models utilizing Adam optimization and a learning parameter set at 0.001, the use of a linear kernel in SVM for brain tumor classification is demonstrated in Table 3.

TABLE 3
ADAM OPTIMIZATION TEST LEARNING RATE 0,001

Model 1	Learning Rate	Optimization	Model 2	Accuracy
CNN	0,001	Adam	-	98.40%
			SVM	98.92%

Table 3 shows the accuracy in testing using the pure CNN model and the CNN-SVM model with Adam optimization and a learning parameter set at 0.001. The testing results were selected based on the highest accuracy achieved. It was found that the CNN-SVM model improved the accuracy compared to the pure CNN model. Specifically, with the CNN-SVM model optimized using Adam with a learning parameter set at 0.001, an accuracy of 98.92% was achieved.

For the accuracy results obtained from tests comparing the pure CNN with the CNN-SVM hybrid models utilizing Adam optimization and a learning parameter set at 0.0001, the use of a linear kernel in SVM for brain tumor classification is demonstrated in Table 4.

TABLE 4
ADAM OPTIMIZATION TEST LEARNING RATE 0,0001

Model 1	Learning Rate	Optimization	Model 2	Accuracy
CNN	0,0001	Adam	-	97.66%
			SVM	98.06%

Table 4 displays the accuracy in testing using the pure CNN model and the CNN-SVM model with Adam optimization and a learning parameter set at 0.0001. The testing results were selected based on the highest accuracy achieved. It was found that the CNN-SVM model improved the accuracy compared to the pure CNN model. Specifically, with the CNN-SVM model optimized using Adam with a learning parameter set at 0.0001, an accuracy of 98.06% was achieved.

For the accuracy results obtained from using the pure CNN model and the CNN-SVM hybrid model utilizing RMSProp optimization and a learning parameter set at 0.001, the use of a linear kernel in SVM for brain tumor classification is shown in Table 5.

TABLE 5
RMSPROP OPTIMIZATION TEST LEARNING RATE 0,001

Model 1	Learning Rate	Optimization	Model 2	Accuracy
CNN	0,001	RMSProp	-	98.46%
			SVM	98.57%

Table 5 shows the accuracy in testing using the pure CNN model and the CNN-SVM model with RMSProp optimization and a learning parameter set at 0.001. The testing results were selected based on the highest accuracy achieved. It was found that the CNN-SVM model did not improve the accuracy compared to the pure CNN model. Specifically, with the CNN-SVM model optimized using RMSProp with a learning rate of 0.001, an accuracy of 98.57% was achieved.

For the accuracy results obtained from using the pure CNN model and the CNN-SVM hybrid model utilizing RMSProp optimization and a learning parameter set at 0.0001, the use of a linear kernel in SVM for brain tumor classification is shown in Table 6.

TABLE 6
RMSPROP OPTIMIZATION TEST LEARNING RATE 0,0001

Model 1	Learning Rate	Optimization	Model 2	Accuracy
CNN	0,0001	RMSProp	-	96.97%
			SVM	98.23%

Table 6 displays the accuracy in testing using the pure CNN model and the CNN-SVM model with RMSProp optimization and a learning parameter set at 0.0001. The testing results were selected based on the highest accuracy achieved. It was found that the CNN-SVM model did improve the accuracy compared to the pure CNN model. Specifically, with the CNN-SVM model optimized using RMSProp with a learning rate of 0.0001, an accuracy of 98.23% was achieved.

D. Evaluasi

In this study, Adam's optimized classification report was used for the evaluation process, with a learning parameter set at 0.001. The testing results analysis involved evaluating a confusion matrix that included metrics for accuracy, precision, recall, and f1-score. The classification report shows how well the model performed on two separate classes. Figure 4 illustrates these findings.

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9888    0.9847    0.9867       717
           1     0.9894    0.9923    0.9908      1035

    accuracy                         0.9892      1752
   macro avg     0.9891    0.9885    0.9888      1752
weighted avg     0.9892    0.9892    0.9892      1752
```

Figure 4. Classification Report Adam, Learning Rate 0,001

Figure 4 depicts results of the classification report for the CNN-SVM hybrid approach using Adam optimization with a learning parameter set at 0.001. The obtained metrics include an accuracy of 0.9892, indicating the model correctly classifies 98.92% of instances overall. Precision is 0.9888, meaning 98.88% of predictions are correct for class not diagnosed. Recall stands at 0.9847, indicating the model identifies 98.47% of actual class not diagnosed instances. The f1-score of 98.67% indicates a balanced measure of recall and precision metrics for the class not diagnosed. Then, for the class diagnosed achieved a precision of 98.94%, recall of 99.23%, and an f1-score of 99.08%.

In this study, Adam's optimized classification report was used for the evaluation process, with a learning parameter set at 0.0001. The testing results analysis involved evaluating a confusion matrix that included metrics for accuracy, precision, recall, and f1-score. The classification report shows how well the model performed on two separate classes. Figure 5 illustrates these findings.

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9763    0.9763    0.9763       717
           1     0.9836    0.9836    0.9836      1035

    accuracy                         0.9806      1752
   macro avg     0.9799    0.9799    0.9799      1752
weighted avg     0.9806    0.9806    0.9806      1752
```

Figure 5. Classification Report Adam, Learning Rate 0,0001

Figure 5 presents results of Adam's optimized classification report with a learning parameter set at 0.0001 using CNN-SVM hybrid approach. The obtained metrics include an accuracy of 0.9806, indicating the model correctly classifies 98.06% of instances overall. Precision is 0.9763, meaning 97.63% of predictions are correct for class 0 (not diagnosed). Recall is also 0.9763, indicating the model identifies 97.63% of actual class not diagnosed instances. The f1-score is 0.9763, demonstrating a balanced measure of precision and recall at 97.63% for class not diagnosed. Then, for the class diagnosed achieved a precision of 98.36%, recall of 98.36%, and an f1-score of 98.36%.

In this study, RMSProp's optimized classification report was used for the evaluation process, with a learning parameter set at 0.001. The testing results analysis involved assessing a confusion matrix that included metrics for accuracy, precision, recall, and f1-score. The classification report illustrates how well the model performed on two separate classes. Figure 6 displays these findings.

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9860    0.9791    0.9825       717
           1     0.9856    0.9903    0.9880      1035

    accuracy                         0.9857      1752
   macro avg     0.9858    0.9847    0.9852      1752
weighted avg     0.9857    0.9857    0.9857      1752
```

Figure 6. Classification Report RMSProp, Learning Rate 0,001

Figure 6 shows results of RMSProp's optimized classification report with a learning parameter set at 0.001 using a CNN-SVM hybrid approach. The obtained metrics include an accuracy of 0.9857, indicating the model correctly classifies 98.57% of instances overall. Precision is 0.9860, meaning 98.60% of predictions are correct for class not diagnosed. Recall is 0.9791, indicating the model identifies 97.91% of actual class not diagnosed instances. The f1-score is 0.9825, demonstrating a balanced measure of precision and recall at 98.25% for class not diagnosed. Then, for the class diagnosed achieved a precision of 98.56%, recall of 99.03%, and an f1-score of 98.80%.

In this study, RMSProp's optimized classification report was used for the evaluation process, with a learning parameter set at 0.001. The testing results analysis involved assessing a confusion matrix that included metrics for accuracy, precision, recall, and f1-score. The classification report illustrates how well the model performed on two separate classes. Figure 7 displays these findings.

Classification Report:

	precision	recall	f1-score	support
0	0.9751	0.9819	0.9785	717
1	0.9874	0.9826	0.9850	1035
accuracy			0.9823	1752
macro avg	0.9812	0.9822	0.9817	1752
weighted avg	0.9823	0.9823	0.9823	1752

Figure 7. *Classification Report* RMSProp, *Learning Rate* 0,0001

Figure 7 displays results of RMSProp's optimized classification report with a learning parameter set at 0.001 using a CNN-SVM hybrid approach. The obtained metrics include an accuracy of 0.9823, indicating the model correctly classifies 98.23% of instances overall. Precision is 0.9751, meaning 97.51% of predictions are correct for class not diagnosed. Recall is 0.9819, indicating the model identifies 98.19% of actual class not diagnosed instances. The f1-score is 0.9785, demonstrating a balanced measure of precision and recall at 97.85% for class not diagnosed. Then, for the class diagnosed achieved a precision of 98.74%, recall of 98.26%, and an f1-score of 98.50%.

Further, the results of the above classification showed that using scenario 1 optimization Adam with a learning rate of 0.001 and using a linear kernel on the SVM classification through testing using data test had the highest accuracy value compared to the use of other research scenarios. Figure 6 shows the results of a brain tumor classification using a CNN-SVM hybrid scenario 1 optimization of Adam with a learning rate of 0,001. Can be seen in Figure 8.

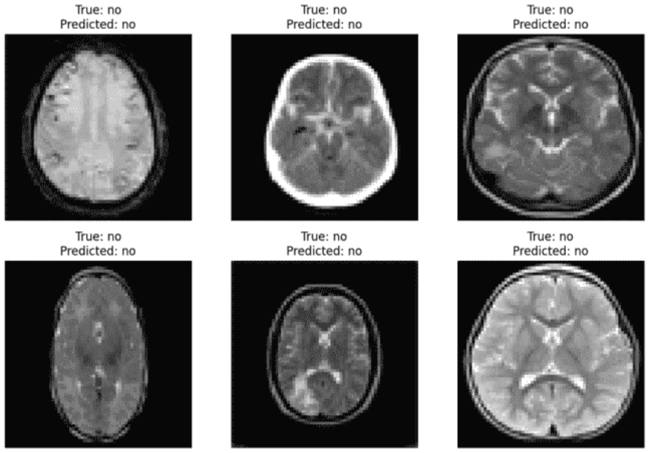


Figure 8. Classification Results CNN-SVM Adam *Learning Rate* 0,001

IV. CONCLUSIONS

According to these findings, the following conclusions are drawn. As a result of the research that has been conducted, the resulting CNN-SVM hybrid model has shown good results with some different optimization and learning rates, compared to the pure CNN model. Thus, increasing the learning rate has the potential to notably enhance the model's accuracy. Results from training with a learning parameter set at 0.001 demonstrated higher accuracy than with a learning parameter set at 0.0001.

With the learning rate set at 0.001 and using Adam's optimization, a higher level of accuracy can be achieved compared to RMSProp. The experiment with the highest accuracy occurred in the CNN-SVM model using Adam optimization and a learning rate of 0.001, with a linear kernel, achieving an accuracy of 98.92%, precision 98.92%, recall 98.92%, and f1-score 98.92%. While using RMSProp optimization and learning rate 0.001 achieved the highest accuracy level of 98.57%, precision 98,57%, recall 98.58%, and f1-score 98.57.

In conclusion, this research indicates that the highest accuracy was achieved during testing with Adam optimization and a learning rate of 0.001. For future research, it is recommended to consider adding kernels for SVM classification and exploring other CNN architectures such as AlexNet for feature extraction. This approach could potentially enhance the classification performance and provide comparative insights into different CNN models' effectiveness for the task at hand.

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