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Investigating the Impact of ReLU and Sigmoid Activation Functions on Animal Classification Using CNN Models

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Abstract

VGG16 is a convolutional neural network model used for image recognition. It is unique in that it only has 16 weighted layers, rather than relying on a large number of hyperparameters. It is considered one of the best vision model architectures. However, several things need to be improved to increase the accuracy of image recognition. In this context, this work proposes and investigates two ensemble CNNs using transfer learning and compares them with state-of-the-art CNN architectures. This study compares the performance of (rectified linear unit) ReLU and sigmoid activation functions on CNN models for animal classification. To choose which model to use, we tested two state-of-the-art CNN architectures: the default VGG16 with the proposed method VGG16. A dataset consisting of 2,000 images of five different animals was used. The results show that ReLU achieves a higher classification accuracy than sigmoid. The model with ReLU in fully connected and convolutional layers achieved the highest precision of 97.56% in the test dataset. The research aims to find better activation functions and identify factors that influence model performance. The dataset consists of animal images collected from Kaggle, including cats, cows, elephants, horses, and sheep. It is divided into training sets and test sets (ratio 80:20). The CNN model has two convolution layers and two fully connected layers. ReLU and sigmoid activation functions with different learning rates are used. Evaluation metrics include accuracy, precision, recall, F1 score, and test cost. ReLU outperforms sigmoid in accuracy, precision, recall, and F1 score. This study emphasizes the importance of choosing the right activation function for better classification accuracy. ReLU is identified as effective in solving the vanish-gradient problem. These findings can guide future research to improve CNN models in animal classification.

Keywords: *convolutional neural network; activation function; sigmoid; relu; classification; images*

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1. Introduction

Image processing and pattern recognition are growing fields in artificial intelligence. In recent decades, these techniques have undergone significant advancements and have been applied in a variety of applications, including face recognition, object detection, action recognition, and image classification. In the context of image classification, the convolutional neural network (CNN) has proven to be one of the most effective and popular algorithms [1], [2]. Previous research, also carried out by Choudhary [3], demonstrated the experimental results that DenseNet121 achieves the highest accuracy detection performance in CLDC. We have also used two more CNN architectures to identify cowpea leaves from weeds, and comparative studies have been conducted and explored in the article. The DenseNet121 method provides an accuracy of 86.12% (training dataset) and 88.89% (testing dataset) respectively.

The research carried out by [4] on the Caltech 101 database found that the classification of object images with different levels of confusion resulted in an accuracy value of 20% - 50%, so it was concluded that the CNN method was relatively reliable for the parameter changes made. In CNN activation functions are used, such as sigmoid and Relu functions. The

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activation function is a non-linear function that allows an Artificial Neural Network (ANN) to be able to transform the input data into a higher dimension so that simple hypeprolane cutting can be performed, which allows classification.

An important aspect of the use of CNNs is the selection of an appropriate activation function. The activation function is used to introduce nonlinearity into the CNN model, which allows this algorithm to model complex relationships between image features and the desired class label [5], [6]. In general, the activation functions used in CNNs are Rectified Linear Unit (ReLU) and Sigmoid [7], [8].

ReLU is a simple yet effective nonlinear activation function. Converts all negative values to zero and retains positive values. The main advantage of ReLU is its ability to overcome the problem of vanishing gradients [9], [10]. Dead gradient is a phenomenon in which the gradient transmitted back to the previous layer becomes very small, resulting in a decrease in convergence speed and poor quality in model training. ReLU can overcome this problem by keeping the gradient large when the input value is positive [11].

Sigmoid is another commonly used activation function in CNNs. This function produces an output in the range of 0 to 1, which describes the probability of a particular class [12]. Sigmoid can be used for binary classification tasks, where an output close to 1 indicates the probability of a positive class, while an output close to 0 indicates the probability of a negative class. However, sigmoids have several drawbacks, including the ability to suffer from dead gradient problems and the tendency to produce outputs far from 0 or 1, which can hinder model convergence [13], [14].

In the context of image processing and image classification, analyzing the performance of selecting the right activation function is very important. The performance of CNN algorithms in classifying animal images can be affected by the selection of activation functions used [15], [16]. However, to date, few studies specifically compare the performance of ReLU and Sigmoid in animal image classification tasks.

Therefore, this study aims to analyze the image processing performance of animal image classification using the CNN algorithm method. This study aims to analyze the image processing performance of animal image classification using the CNN algorithm method [17], [18]. The main focus of this research is to compare two popular activation functions in CNN, namely the Rectified Linear Unit (ReLU) and the Sigmoid, to determine which of them is the most effective in classifying animal images [19], [20].

The dataset used in this study consists of animal images, including cats, cows, elephants, horses, and sheep. The dataset covers a wide variety of animal images, including different poses, backgrounds, and lighting conditions [21], [22]. The data have been carefully collected and curated to reflect the diversity that can be encountered in real-world animal image classification tasks [23].

The method used in this research involves the use of an optimized CNN to improve classification performance. CNNs are a type of neural network inspired by the visual structure of the human cortex. CNN architecture consists of convolutional layers to hierarchically extract image features and fully connected layers to classify the image. At each layer, an activation function is applied to introduce nonlinearity into the processing process [24], [25]. Experiments were conducted by applying ReLU and Sigmoid activation functions to CNN layers to compare their performance in classifying animal images.

Performance measures used include classification accuracy, which is the percentage of correctly classified images, and computation time, which reflects the efficiency of using activation functions in image processing [26], [27]. The results of this study are expected to provide better insight into the selection of activation functions in the context of animal image classification using the CNN algorithm. This research is expected to reveal the advantages and disadvantages of each activation function, as well as provide recommendations on the optimal use of both in animal image classification tasks [28], [29].

With a better understanding of the role of activation functions in image processing and image classification, this research has the potential to make important contributions to the development of more effective and efficient CNN-based image recognition systems. In addition, the findings of this study can be used as a basis for further research development in the fields of artificial intelligence and pattern recognition [3], [30].

The method that will be used in this study is an experiment by varying the activation function on CNN and measuring the accuracy, recall, precision, and F measure of the classification produced by each activation function. In addition, the results obtained will be analyzed to compare the performance of the two activation functions, as well as the selection of hyperparameter values and the use of Adam optimization.

In the next chapter, we will discuss more about the basic theory related to CNN, sigmoid, and relu activation functions, as well as related research that has been done before. In addition, it will also explain the dataset used in this study and the methods that will be used to process and analyze the data.

The urgency of this research lies in the growing fields of image processing and pattern recognition within artificial intelligence. With advancements in these techniques, application areas have expanded to include face recognition, object detection, action recognition, and image classification.

In particular, the Convolutional Neural Network (CNN) has emerged as a highly effective algorithm for image classification tasks. However, a crucial aspect that significantly influences CNN performance is the selection of an appropriate activation function. In conclusion, this research addresses the urgent need to evaluate and compare the performance of ReLU and sigmoid activation functions in animal image classification using CNN algorithms. The anticipated results will facilitate informed decision making regarding the selection and utilization of activation functions, providing valuable information for future advances in artificial intelligence and pattern recognition.

2. Research Methods

2.1. VGG16 Architecture CNN Method

VGG16 is a convolutional neural network (CNN) architecture that is considered one of the best vision model architectures to date. Instead of having a large number of hyperparameters, VGG16 uses a convolution layer with a 3x3 filter and step 1 that sits on the same padding and maxpool layers of the 2x2 filter step 2. The arrangement of the convolution layers and the maximum pool across the architecture follows. In the end, it has two fully connected layers, followed by softmax for the output. The 16 in VGG16 refers to the 16 weighted layers. This network is quite a large network and has around 138 million (approximately) parameters. The following is the flow diagram of this research carried out for the development of the proposed VGG16 architectural model.

This flow chart outlines the main steps involved in the investigation. It starts by collecting an animal image dataset that is then divided into training and testing sets. Two separate CNN models are developed, one with the ReLU activation function and another with the sigmoid activation function. The models are trained using the training dataset and evaluated using the testing dataset. The classification results are analyzed and performance metrics such as accuracy, precision, recall, and the F1 score are compared for both activation functions. Statistical analysis is conducted to conclude the findings. A research report is written on the basis of the results, followed by finalizing and submitting the research findings.

Based on Figure 1, the program flowchart illustrates the steps involved in data sharing, data processing, designing the CNN model incorporating activation functions as non-linearities, determining the accuracy results of the CNN algorithm, and conducting tests to evaluate the accuracy when combined with various activation functions. At this stage, a comparative analysis of the activation functions of ReLU and Sigmoid will be conducted. The subsequent process showcases the accuracy of the training and validation, as well as the results of the training and validation loss.

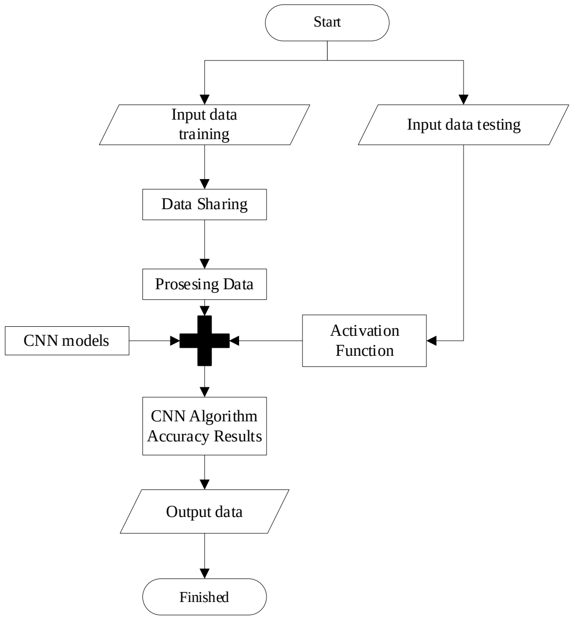


Figure 1. Research Flowchart

2.2. Dataset

The dataset used in this study consists of animal images that have been collected from Kaggle. This dataset consists of several types of animals, including cats, cows, elephants, horses, and sheep. A total of 2801 images were used as test material in analyzing the CNN optimization model on the activation function and the use of different batch-size hyperparameters. The data are divided into 2 parts of data processing to get the expected results, namely training data and testing data. For training data using 2301 images and data testing using 500 images. An example of data can be seen in Figure 2.

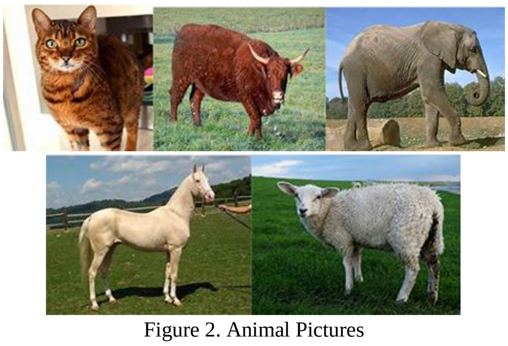


Figure 2. Animal Pictures

According to InfoWorld, Kaggle is an online community formed by Anthony Goldbloom as the CEO and Ben Hamner as the CTO in 2010. This online community hosts data scientists who want to learn more about machine learning and other related sciences. In it, various activities are carried out, one of the most famous of which is the machine learning competition. Kaggle itself states that, apart from competing, members of its community can co-write and share code and learn various things. Data scientists can also earn money from projects offered on Kaggle.

2.3. Pre-processing Data

Before the CNN training process is performed, the data must be processed first. The pre-processing process carried out in this study is to change the image size to the same size and normalize the pixel values. By cropping the image by 20%, providing an image rotation of 15 degrees, and flipping the image into two rotations, namely horizontal and vertical.

2.4. Training Process

The CNN training process is carried out by varying the activation functions of the sigmoid, ReLU, and softmax on the convolution layer and the fully connected layer. The use of different batch-size hyperparameters. Each model will be trained using the backpropagation algorithm, and its accuracy will be measured on the validation dataset.

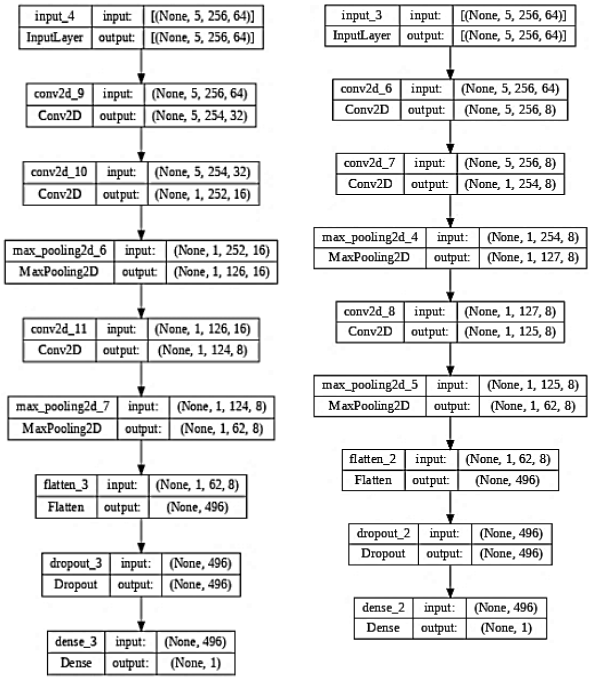
2.5. Model Evaluation

After the training process is completed, an evaluation of each model is performed by calculating the classification accuracy of the test dataset. In addition, the results obtained will be analyzed to compare the performance of the two activation functions. The model presented has hyperparameter values and different kernel size features.

2.6. Results of Model Testing

This research will use Python and several libraries such as TensorFlow, Keras, and NumPy to carry out the training and evaluation process on CNN. The test results were obtained after testing, which was assisted by the pytorch programming used by the author. The architectural model, the hyperparameter values and the use of layers in the ReLU model can be seen in Figure 3.

Using the configuration in Figure 3 a, the CNN model will be trained using data of size 60 with 64 features (attributes) to predict 5 stocks. Training will be done in batches of size 128 as long as no overfitting occurs. With several layers of 4, kernel size of 3, and the use of a layer that receives input in the form of an image with 3 color channels, goes through a convolution layer with ReLU and max pooling activation functions, and finally produces output in the form of a one-dimensional vector ready to be used by the next linear or fully connected layer in the model. And produce an output with 8 channels.
In Figure 3b Using this configuration, the CNN model will be trained using data of size 60 with 64 features (attributes) to predict 5 stocks. Training will be carried out in batches of size 64 as long as there is no overfitting. With the number of layers 3, kernel size 1, and the use of a layer that accepts input in the form of images with 3 color channels, passes the convolution layer with the Sigmoid activation function and max pooling, and finally produces output in the form of a one-dimensional vector that is ready for use by linear or connected layers. next full in the model. And produce output with 8 channels.



a. ReLU b. Sigmoid

Figure 3. (a). the ReLU architectural model, (b). sigmoid architectural model

3. Results and Discussions

3.1. Results

This test uses two activations, namely the ReLU activation function with a learning rate of 0.001 and the Sigmoid learning rate activation function of 0.01 with parameters namely batch size 128 for ReLU and 64 for sigmoid, for Epoch here using an early stop, where when the model cannot get accuracy and loss again, the process automatically stops.

The performance metrics obtained from the evaluation of the ReLU and Sigmoid models are critically analyzed. Comparative analysis reveals potential differences in the models' ability to classify animal images accurately. Statistical tests are conducted to determine the significance of these differences, providing robust evidence to support the findings.

Based on observed patterns and statistical analyzes, conclusions are drawn about the specific impact of ReLU and Sigmoid activation functions on animal classification using CNN models. Insights into the strengths and weaknesses of each activation function are highlighted, helping researchers and practitioners make informed decisions when selecting activation functions for similar image classification tasks.

Figure 4 shows a graph of the results of the training process and the testing of the ReLU and Sigmoid activation data for good CNN, the red graph shows the training process and the blue graph shows the consistent touching testing process which shows that the work model is not overfit. So, in this model, the epoch is not limited; the epoch will stop automatically if there is no progress back in the test with the early stopping function.

The cosine distance does not change for input rescaling, which, when combined with the ReLU and sigmoid equivalents, makes the entire model analytically invariant for rescaling from pixels with positive scalars. Variants apply regardless of the number of ReLU and sigmoid layers, so it is possible to train deep architectures with these properties.

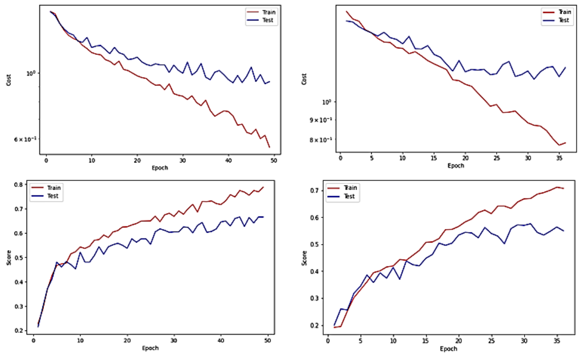


Figure 4. a. ReLU (**left**); b. Sigmoid (**right**): Graph of ReLU and Sigmoid Activation Functions

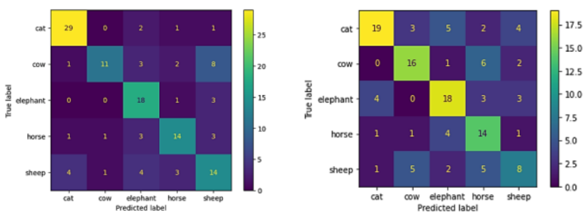


Figure 5. a. ReLU (**left**); b. Sigmoid (**right**): Confusion Matrix ReLU and Sigmoid

Figure 5 shows a plot of the results of the confusion matrix of the training process using two optimization activations. On the left side of the plot are the True Labels of the five animal classes, which are the actualization of the actual animal classes, and at the bottom are the Predicted labels, which are predictions of the training process. To see how the prediction visualization results from the built model will be displayed in the form of an image. As explained in the previous explanation, the image data taken were 128 images.

To set the display, dimensions of 5 rows and 8 columns are used, which only display 40 images. The following is a picture of ReLU activation, which is the result of a comparison, ReLU activation is quite good for the final results in accuracy, recall, precision and F1 score, which are the parameters used by the author.

The ReLU matrix has the advantage of more efficient computation as it only needs to check whether the matrix element values are positive or negative. This can save computational time and system resources. The sigmoid matrix has a more complex computation as it involves exponential operations, which can take more time.

In the case of large matrices, this can have an impact on the system performance. The ReLU matrix has the advantage of easier gradient removal. When the gradient flows backwards in an artificial neural network, neurons with negative values in the ReLU matrix have zero gradients, so they can be effectively "eliminated" from the calculation, which speeds up the training of the network. Sigmoid matrices do not have the same gradient removal. Neurons with sigmoid values close to 0 or 1 have very small gradients but do not become zero.

This can lead to vanishing gradient or exploding gradient problems when performing deeper network training. The ReLU matrix is often used in artificial neural networks with deeper and more complex architectures, such as Convolutional Neural Networks (CNNs) for image recognition tasks. The ReLU matrix can help the network learn more complex and non-linear features. Sigmoid matrices are often used in artificial neural networks for binary classification problems, where the desired output is the probability of different classes. For example, in text sentiment recognition tasks, sigmoid matrices can generate positive or negative probabilities for each inputted text.

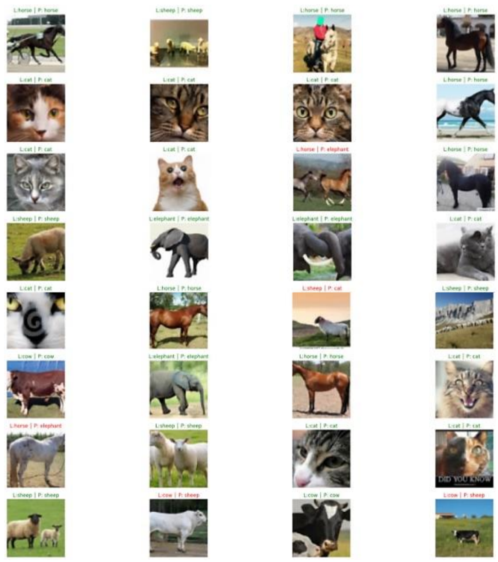


Figure 6. Predicted Image Visualization Using CNN with ReLU activation

In Figure 6 it can be seen that the actual label will be compared with the predicted label, where if the actual label and the predicted label show the same class, it will be green, in other words, true positive. And if the actual label and predicted label show a different class, it will be a False Positive in red. Prediction errors can occur due to image factors which can be caused by several factors such as test data in this case in the form of unclear images, background influences such as properties, similarity of colors and shapes, and so on. In the first row fourth column example, there is a decapitated tiger, and the larger machine is represented by an elephant. This can be overcome by adding a tiger image without head to the training data. After performing the training and evaluation process on CNN by varying the activation functions of the sigmoid and ReLU, the following results are obtained.

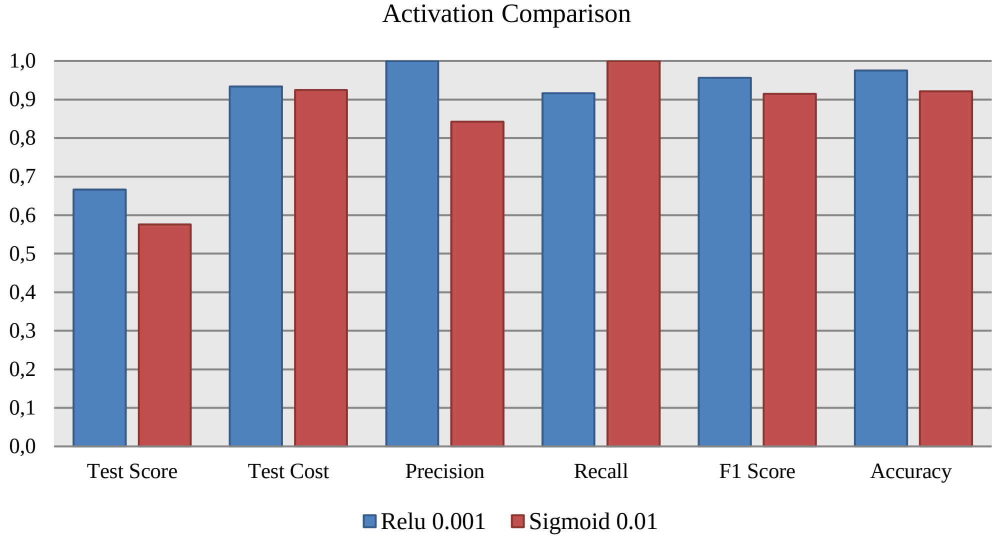


Figure 7. Comparison of ReLU and Sigmoid Activation Optimization Results

In Figure 7. we can see that for accuracy, recall, precision, and F1, the highest score is in the ReLU activation model with an accuracy level of 97% and 92% for Sigmoid. We can see this in Table 1.

Table 1. Results of a Comparison of ReLU Activation Against Learning Rate

Activate	Test Score	Test Cost
ReLU	0,6660	0,9338
Sigmoid	0,5760	0,9244

Activate	Precision	Recall	F1 Score	Accuracy
ReLU	1,0000	0,9167	0,9565	97,56%
Sigmoid	0,8421	1,0000	0,9143	92,11%

Table 1 shows the comparison between the use of ReLU and sigmoid activation functions in a CNN model with different learning rates. It can be seen that the model with ReLU activation in both convolution and fully connected layers has the highest classification accuracy of 97,56% in the test dataset, while the model with sigmoid activation has a classification accuracy of 92%. Additionally, ReLU also shows better results in precision, recall, and F1 score compared to sigmoid.

These results are consistent with previous studies that have shown that the use of the ReLU activation function can improve the performance of CNN models in image classification tasks compared to the sigmoid. The ReLU function can overcome the problem of vanishing gradients that occurs in models with many layers, allowing for more effective training and producing more accurate results.

However, it should be noted that these results still need to be considered with other factors, such as dataset size, data complexity, and other parameter settings on CNN that can affect the model's performance. Therefore, more research is needed to improve and validate the results obtained considering various important factors that influence the performance of the model in animal classification using CNN.

3.2. Discussion

Based on the results presented in Table 1, the ReLU activation function performed significantly better than the sigmoid activation function in terms of classification accuracy, with the former achieving an accuracy of 97,56% compared to the latter's 92%. Furthermore, the ReLU activation function is more effective in mitigating the vanishing gradient problem commonly encountered in CNNs, which can hinder the training process and affect the overall performance of the model.

However, it is important to note that the results obtained in this study were based on specific parameter settings and may be influenced by other factors such as the size of the dataset and the complexity of the data. Therefore, more research is needed to explore the impact of these factors on the performance of CNN models using different activation functions. Overall, the findings suggest that the use of the ReLU activation function in the convolution and fully connected layers can improve the accuracy of animal classification using CNN. However, researchers should be aware of other factors that can affect the performance of the model and consider conducting more experiments to validate and improve the results.

This research study provides comprehensive information on the impact of Rectified Linear Unit (ReLU) and Sigmoid activation functions on animal classification using Convolutional Neural Network (CNN) models. The findings reveal specific performance differences between the ReLU and Sigmoid models, demonstrating the influence of activation functions on the accuracy and effectiveness of animal classification.

These insights have significant implications for various domains, including wildlife conservation, veterinary diagnostics, and automated image analysis tasks. More research is encouraged to explore additional activation functions and investigate their impact on similar classification tasks in diverse domains. In general, this study provides valuable information for researchers and practitioners working on image classification using CNN models, helping them select the appropriate activation functions to achieve optimal performance.

4. Conclusions

This study successfully highlights the importance of choosing the activation function in CNN architectures, particularly in the context of animal classification. Using a modified VGG16 model, this research explores a comparison between ReLU and sigmoid activation functions in two CNN architectures. The results indicate that ReLU outperforms sigmoid in terms of accuracy, precision, recall, and F1 score, with the highest accuracy reaching 97.56%. These findings affirm the significance of ReLU in addressing the issue of vanishing gradients, which is a major contribution of this research. We acknowledge that this study has limitations. One is the use of a limited dataset comprising only 2,000 images of five types of animals. Therefore, the results may not fully reflect the performance under more diverse and complex conditions. Additionally, this study focuses on two activation functions with specific parameter settings, which may not encompass the entire spectrum of possible configurations in animal classification practice. For future research, further exploration of dataset variations, including a larger number of images and more diverse types of animals, is highly recommended. This would provide deeper insight into the scalability and adaptability of the model. Furthermore, research on the impact of combining other activation functions and further parameter adjustments could offer a more comprehensive understanding of optimizing CNN models for animal classification. Overall, this study makes a significant contribution to understanding the impact of activation functions on animal classification using CNN models. These findings can help develop more accurate and efficient models for future image recognition applications.

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