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Classification of Foot and Mouth Diseases (FMD) in Cattle using DenseNet-CBAM

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Abstract

Foot-and-mouth disease (FMD) poses a serious threat to Indonesia's livestock sector as it impacts the productivity and distribution of livestock, particularly cattle. Early detection of FMD symptoms still relies on visual methods that are inaccurate and time-consuming. This study aims to develop an automatic classification system based on the DenseNet-CBAM model to detect FMD symptoms in cattle through digital images. The dataset used was obtained from the Bojonegoro District Livestock and Fisheries Service, consisting of 180 images, and expanded through augmentation to 2,000 images. The preprocessing process included determining the region of interest (ROI), augmentation, data splitting, and resizing the images to 150x150 pixels. The model architecture combines DenseNet169 with the Convolutional Block Attention Module (CBAM) to enhance the model's focus on important spatial features. Model evaluation was conducted using accuracy, precision, recall, and F1-score metrics. The best results were obtained with a data split configuration of 70:15:15, a batch size of 16, and 50 epochs, achieving an accuracy of 94% and average precision, recall, and f1-score values of 0.94. This study demonstrates that the combination of DenseNet and CBAM is effective for the automatic early detection of PMK.

Keywords– *Cattle, CBAM, DenseNet, Diseases, FMD*

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1. Introduction

Livestock farming is an important sector of global agriculture, providing meat, dairy, and livelihoods for millions of people around the world (Shinde et al., 2024). In Indonesia, this sector has considerable potential, with leading commodities including dairy and beef cattle. Both leading commodities develop in a concentrated production center development area (Kusuma Pradana et al., 2019). In rural areas, cattle are one type of livestock that is generally raised by local farmers (Muzakkir & Botutihe, 2020). However, the health and welfare of livestock, especially cattle, is often threatened by various diseases that can have an impact on the productivity, welfare and economic stability of farmers.

One of the main threats to cattle farming is foot and mouth disease (FMD), an infectious disease that affects cloven-hoofed animals such as cattle, pigs, sheep and goats (Grubman & Baxt, 2004). FMD virus or in foreign terms Foot and Mouth Diseases Virus (FMDV) is an unenveloped RNA virus that belongs to the genus Aphthovirus of the Picornaviridae family (Domingo et al., 2003). The virus has seven major serotypes, namely serotypes A, O, C, Asia 1, SAT1, SAT2, and SAT3, which can cause serious infections in cattle (Knowles & Samuel, 2002). Common symptoms found in infected cattle include fever, lameness, lesions on the mouth, tongue and feet, as well as weight loss due to anorexia, and discomfort when moving. The impact on cattle production is a decrease in milk and meat production and disruption in the livestock distribution and trade system due to restrictions on animal trade (Chen et al., 2020).

Efforts to prevent FMD, including in cattle in Indonesia, have been carried out through mass vaccination, but slow early detection remains a major challenge (Phulu et al., 2024). FMD detection based on the traditional method of visual inspection by veterinarians has limitations in terms of accuracy and speed, potentially causing delays in outbreak control (Maulina et al., 2023). In addition, new diseases can often spread before clinical symptoms are apparent, which increases the risk of wider outbreaks and mass mortality (Mehta & Khurana, 2024). Therefore, the development of an automatic detection system based on artificial intelligence (AI) and computer vision technology can act as a tool to support early detection of FMD more quickly and accurately, thus complementing conventional methods such as visual inspection by veterinary medical personnel, such as doctors or animal orderlies.

One of the technology-based approaches in livestock disease detection is the application of artificial intelligence (AI) and computer vision. One method is the DenseNet-CBAM model, which combines the Dense Convolutional Network (DenseNet) architecture with the Convolutional Block Attention Module (CBAM). DenseNet has a network structure that utilizes deeper connectivity to improve information propagation and overcome the missing gradient problem with the use of fewer parameters (Mujahid et al., 2024). Meanwhile, CBAM allows the model to focus more on relevant features in the image by applying adaptive attention to spatial and channel dimensions, thus improving classification accuracy (Woo et al., 2018). Research related to foot and mouth disease (FMD) detection using DenseNet-CBAM is still very limited, especially in the context of livestock farming in Indonesia. This study aims to develop an early detection model of FMD symptoms that is adapted to the typical characteristics of FMD such as wounds on the mouth, hooves, and snout of cattle.

2. Method

The research method consists of seven main stages in the process of developing a DenseNet-CBAM model for the classification of foot-and-mouth disease in cattle, which can be seen in Figure 1.

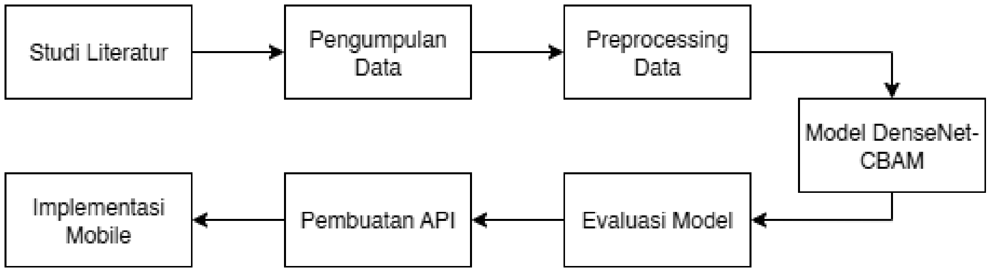

Figure 1. Research Flow

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The initial stage of the research was to conduct a literature study to understand the concepts and technologies relevant to the early detection of foot and mouth disease (FMD) in cattle using deep learning models. The literature reviewed includes previous research, theories related to the DenseNet-CBAM model, and the technology used in the implementation of the model.

In this research, the image dataset is obtained through data collection at the Livestock and Fisheries Service Office of Bojonegoro Regency, the data includes images of healthy and FMD infected cows, each cow image has a JPG format with a size of 3000x4000 pixels with a total data of 180 images, consisting of 80 images of FMD infected cows and 100 images of healthy cows. An example of the dataset used is shown in Figure 2.

Figure 2. Sample Dataset

At this stage the image data is further processed so that the data is ready to be used in the development of machine learning models. The data preprocessing stage is carried out before the model training and evaluation process, this research uses data preprocessing as in Figure 3 which includes determining the region of interest (ROI), data augmentation, data splitting, and resizing.

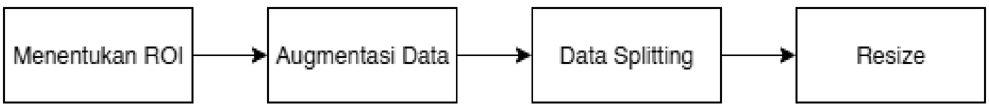

Figure 3. Data Preprocessing Flow

At this stage the image data is further processed so that the data is ready to be used in the development of machine learning models. The data preprocessing stage is carried out before the model training and evaluation process, this research uses data preprocessing as in Figure 3.4 which includes determining the region of interest (ROI), data augmentation, data splitting, and resizing.At this stage the image data is further processed so that the data is ready to be used in the development of machine learning models. The data preprocessing stage is carried out before the model training and evaluation process, this research uses data preprocessing as in Figure 3.4 which includes determining the region of interest (ROI), data augmentation, data splitting, and resizing. This section discusses the performance testing of the developed model.

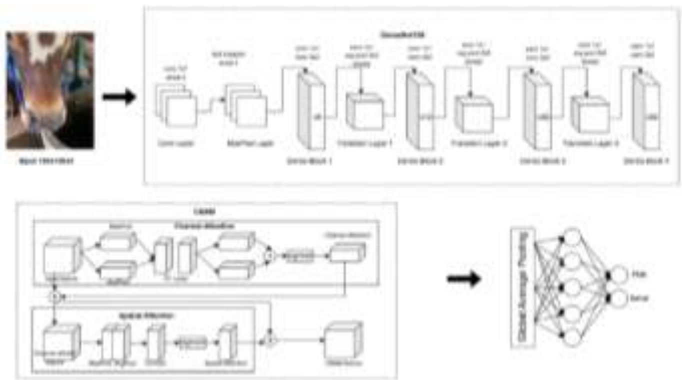

Figure 4. DenseNet-CBAM Model

Testing is conducted using test data to obtain information related to the level of prediction accuracy on all test datasets. The test results will include accuracy, loss and confusion matrix values, including evaluation metrics such as precision, recall, and f1-score.

3. Result and Discussion

The dataset used in this study consists of two types of data, namely primary and secondary data. Primary data was obtained from the Livestock and Fisheries Service Office of Bojonegoro District. This data includes images of healthy and infected cattle with foot and mouth disease (FMD), so it has high relevance to real

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conditions in the field. Figure 5 is an example of the primary dataset used in this study.

Figure 5. Dataset Sample

At this stage the image data is further processed so that the data is ready to be used in the development of machine learning models. The data preprocessing stage is carried out before the model training and evaluation process, this research uses data preprocessing as in Figure 3.4 which includes determining the region of interest (ROI), data augmentation, data splitting, and resizing.

a. Determining the ROI

Determining the Region of Interest (ROI) is done by selecting relevant and important parts of the image for the detection process, in this case, the mouth and hoof of the cow. The ROI selection aims to focus the model only on areas that have key diagnostic information related to disease symptoms, and discard other information that is not needed. The ROIs were manually drawn using the Figma application by cutting out certain areas in the original image as shown in Figure 6.

Figure 6. Determining ROI

b. Data Augmentation

Data Augmentation is applied to increase the number and variety of images, so that the model can learn better and improve model accuracy. Figure 7 shows the augmentation techniques used including Rotation, Zoom, Shift, Shear and Horizontal Flip. In this study, each original image is given several different augmentations, so that the total number of images increases significantly, namely FMD class images to 1500 images and Healthy class to 1200 images.

Figure 7. Sample Data Augmentation

c. Data Splitting

Data Splitting divides the data into 3 parts: training data, validation data, and test data. This division is done to ensure the model can be trained, validated, and tested with different datasets, so that the performance of the model can be evaluated accurately and reduce the risk of overfitting or underfitting. Training data is used to train the model to recognize patterns in the dataset. Next, validation data is used during the training process to evaluate the model's performance on data that has never been seen before. Finally, test data is the dataset used to test the accuracy of the model. In this research, the data is divided into three schemes namely 80:10:10, 70:15:15, and 60:20:20 to get the best results.

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d. Resize

Resize or change the size of the image so that each image has uniform dimensions and fits the input model. The size used in this research is 150x150 pixels. Comparison between the original resized images can be seen in Figure 8.

Figure 8. Resize Result

Table 1. Hyperparameter Setting

Hyperparameter	Value
Splitting Data	70:15:15
Batch Size	16
Epoch	50
Learning Rate	0,00001

After the data preprocessing stage, the next step is to build the DenseNet-CBAM model. The proposed model uses two phases, the first phase features of the cow image are extracted using DenseNet169. In the second phase, the feature extraction results are reinforced with CBAM.

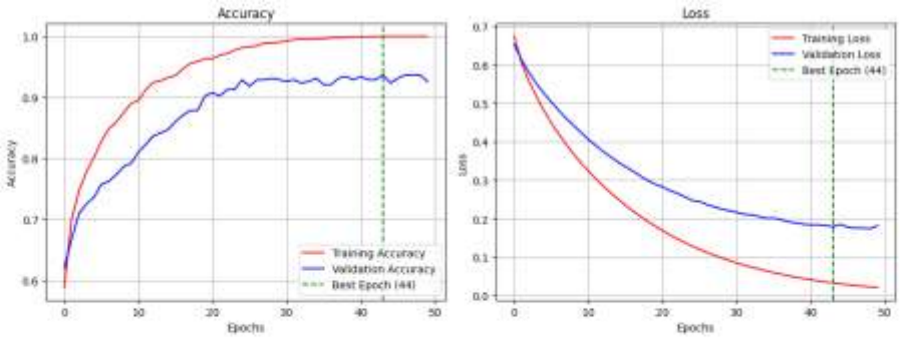

Figure 9. Training Chart

Figure 9 shows the accuracy and loss graphs for 50 training epochs in the 80:10:10 data splitting scenario. The training accuracy experiences a steady and significant increase to close to 100%, while the validation accuracy also increases until around the 44th epoch with a value close to 95%, then tends to stabilize and fluctuate slightly. The loss graph shows that the training loss continues to decrease consistently, while the validation loss decreases more slowly and starts to level off after about the 30th epoch. The peak validation performance is reached at the 44th epoch, which is marked as the best epoch, before the potential for overfitting becomes apparent from the difference between training loss and validation loss. Training is automatically stopped at the 50th epoch through the early stopping method, with the model weights restored to the best state at the 44th epoch to ensure optimal generalization.

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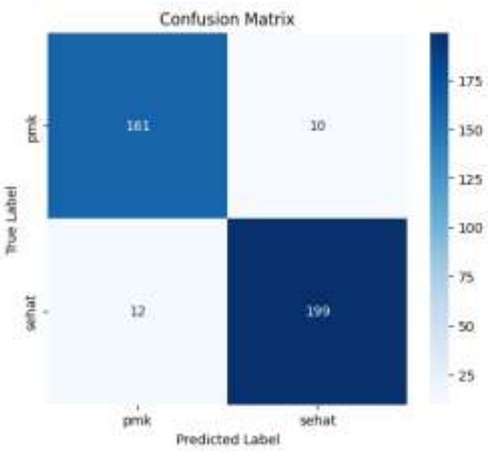

Figure 10. Confusion Matrix

Figure 10 shows the confusion matrix of the evaluation results of the two-class classification model, namely pmk and healthy. The model successfully classifies most of the images correctly, with the number of correct predictions in the pmk class being 161 images and the healthy class being 199 images. There were 10 pmk images misclassified as healthy, and 12 healthy images misclassified as pmk. While both classes showed excellent classification performance, the healthy class was slightly ahead in the number of correct predictions. This misclassification is likely due to the visual similarity between the images of FMD-affected and healthy cattle. Overall, the model showed excellent classification performance with a low error rate.

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Classification Report:
              precision    recall  f1-score   support

         pmk       0.93      0.94      0.94       171
       sehat       0.95      0.94      0.95       211

    accuracy                           0.94       382
   macro avg       0.94      0.94      0.94       382
weighted avg       0.94      0.94      0.94       382
```

Figure 11. Classification Report

Based on the classification model evaluation results shown in Figure 11, it is known that the overall accuracy of the model reaches 94% of the total 382 test data. In addition to accuracy, evaluation is also carried out using the precision, recall, and f1-score metrics for each class to provide an overview of the model's performance in classifying the pmk and healthy categories in more detail. The pmk class obtained a precision value of 0.93, recall of 0.94, and f1-score of 0.94. These values indicate that the model is able to detect and classify images of cattle with foot-and-mouth disease well. Meanwhile, the healthy class recorded a precision of 0.95, recall of 0.94, and f1-score of 0.95, indicating that the model is also quite reliable in recognizing healthy cattle images. Overall, the average values of precision, recall, and f1-score in both macro average and weighted average reached 0.94. This indicates that the model has good classification performance and is relatively balanced in distinguishing between the two classes in the test data.

4. Conclusion

The system was successfully developed from the preprocessing stage, construction of the DenseNet-CBAM model, API integration using flask, to implementation in a flutter-based mobile application that can make predictions from images directly. The DenseNet-CBAM model shows excellent classification performance in detecting FMD symptoms in cattle. Based on the training results, the model achieved 99% accuracy, with precision, recall, and f1-score of 0.94 each. Based on a series of testing scenarios, the best configuration was obtained, namely data splitting 70:15:15, batch size 16, and number of epochs 50.

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