Dairy Cows Teat-End Condition Classification Using Deep Learning

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1 Introduction

Mastitis is a commonly occurring disease in dairy cows which is caused by infections in their mammary glands via the teat canal. However, accurately determining the severity of Mastitis from images can prove to be a challenging task. Previous studies have utilized GoogLeNet transfer learning and Separable Confident Transductive Learning to classify hyperkeratosis severity with a four-level classification scheme, yielding accuracy rates ranging from 46.7

In this study, a novel deep learning model has been proposed that utilizes various architectures such as CNNs, Inception, and Resnets to improve the accuracy of Mastitis severity classification. The approach also employs a technique called pseudo-labeling adjustment, which involves retraining the model using high-confidence images that were correctly predicted. This fine-tunes the network and improves its accuracy. The aim of this study is to develop an efficient and effective approach for precisely classifying the severity of Mastitis in dairy cows.

2 Related Work

2.1 Transductive learning

Transductive learning is a machine learning technique that uses both labeled training data and unlabeled test data to improve classification performance. The primary objective is to find an appropriate function that utilizes the unlabeled data to improve predictions for specific, unlabeled data points. This method considers the predicted labels for the test samples as optimization variables that can be iteratively updated in the training process.

Transductive learning is beneficial in scenarios where there is a limited amount of labeled data available. It enables the model to use the existing labeled data to make predictions for a specific set of unlabeled data points, rather than training on the entire dataset. This feature makes it highly useful in semi-supervised learning situations.

2.2 Pseudo Labeling

Pseudo Labeling is a technique used in semi-supervised machine learning where a model is initially trained on a small set of labeled data. Then, the model is used to predict labels for a larger set of unlabeled data. These predicted labels are then combined with the labeled data set, and the model is retrained on the entire combined set.

In the study, images with high-confidence predictions by the model were identified and used for retraining. This process fine-tunes the network and ultimately improves its accuracy.

3 Methods

3.1 Motivation

Mastitis is a costly and common disease in dairy cows, and accurately identifying its severity through image classification is a significant challenge. My objective is to create a unique deep learning model that utilizes various architectures, including CNNs, Inception, and Resnets, to enhance the accuracy of Mastitis severity classification. Additionally, the model will incorporate the pseudo-labeling adjustment technique to fine-tune the network and further improve its accuracy

3.2 Neural Network

The CNN model is a type of deep neural network used for image classification tasks. It is composed of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The input to the model is a three-channel image, and the output is a softmax probability distribution for each class. The network is designed to extract features from the input image using convolutional and pooling layers, and then use a series of CNN blocks to generate an abstract feature representation for classification.

The CNN block is a specialized building block consisting of two convolutional layers with batch normalization and ReLU activation in between. The output of the second convolutional layer is added to the input of the block, allowing the network to learn residual mappings that bypass the identity mapping. This helps to prevent the problem of vanishing gradients, which can occur in very deep networks, and enables the network to learn deeper and more complex features. The CNN block is used in the model to further refine the features extracted by previous layers, resulting in better classification performance.

The architecture of the CNN model is designed to learn features at different scales and combine them effectively to recognize complex patterns in the input data. This is accomplished through the use of multiple convolutional layers with different kernel sizes, which allow the network to capture both fine-grained and coarse-grained features at the same time. The model also includes batch normalization layers, which normalize the inputs to each layer, reducing the internal covariate shift and improving the network's training speed and performance. Overall, the CNN model is a powerful architecture for image classification tasks, leveraging convolutional and residual blocks to learn complex features and achieve high accuracy in classification.

To make predictions with the CNN model, the input data is passed through the model's forward function.

4 Results

The Cow Test software was used to determine the accuracy of the model on the test dataset, resulting in an accuracy score of 59.63 percent. While this score suggests that the model performed reasonably well on the test dataset, further optimization may be necessary to improve its accuracy. It's important to note that accuracy ratings can vary depending on the dataset and evaluation metrics used, so it's recommended to evaluate the model's performance across multiple metrics and datasets to fully understand its capabilities.

5 References

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