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Cattle Breed Classification Techniques: Framework and Algorithm Evaluation

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Abstract:-Cattle farmers having cattles from different regions may have different vaccines requirements due to variations in their genetic makeup, environmental conditions, and disease prevalence. This research study focuses on efficiently classifying Cattles into their respective breeds using various machine learning frameworks and algorithms. The study utilized a dataset of images representing different cattle breeds.Pytorch and Tensorflow frameworks, along with algorithms such as Residual Network (ResNet), Convolutional Neural Network (CNN), Support Vector Machines (SVM), Principal Component Analysis (PCA), Random Forest, and K-Nearest Neighbors (KNN) have been used for classificaion of cows. To evaluate the efficiency of these frameworks and algorithms, the study used several machine learning parameters, including Precision-Recall Curve, Learning Curve, Feature Importance, ROC Curve, Accuracy, Precision, Recall, and confusion matrix. The research findings suggest that machine learning techniques can be highly beneficial in accurately classifying cattle breeds, with potential applications in animal breeding, veterinary research, livestock management, and online cattle trading. As the demand for effective livestock supply chain tracking and identification systems increases, this research holds implications for enhancing biosecurity and food safety regulations. Notably, the Pytorch framework demonstrated the best performance among the tested classification models, achieving an impressive accuracy rate of 87.6%.
Keywords:*Cattle Breed Classification; Convolutional Neural Network; Livestock Farming Classification*

1. Introduction

Cattle farming play a significant role in the agricultural sector and the economy of many countries around the world. The identification and classification of cattle breeds are essential for effective management and breeding programs. Traditional methods of cattle breed classification rely on visual inspection, which can be subjective and time-consuming. With the advancement of computer vision and machine learning techniques, automated classification of cattle breeds has become possible. However, there is a need for a comparative study to identify the most effective framework or algorithm for cattle breed classification. The traditional methods of cattle breed classification based on visual inspection are subjective and time consuming. Automated classification using computer vision and machine learning techniques can improve the accuracy and speed of cattle breed identification. However, there is a need to compare the effectiveness of various frameworks and algorithms for cattle breed classification to identify the most suitable method for accurate and efficient classification.

The purpose of this study is to compare the performance of different frameworks and algorithms for cattle breed classification. The study aims to identify the most effective method for accurate and efficient cattle breed identification using computer vision and machine learning techniques.

The results of this study will provide valuable insights into the most effective framework or algorithm for cattle breed classification, which can improve the accuracy and efficiency of cattle management and breeding programs. The study will also contribute to the development of automated systems for cattle breed classification, which can reduce the workload and improve the productivity of farmers.

The study will focus on comparing the performance of various frameworks and algorithms for cattle breed classification using a dataset of cattle images. The study will be limited to the evaluation of the accuracy and efficiency of the classification methods and will not cover other aspects of cattle management and breeding programs. The study may also be limited by the availability and quality of the dataset and the computational resources required for the evaluation.

2. Literature Review

Cattle farming is a crucial aspect of the agricultural sector and economies worldwide. The identification and classification of cattle breeds are essential for effective management and successful breeding programs. Traditionally, cattle breed classification has relied on subjective and time-consuming visual inspection methods. However, with the advancement of computer vision and machine learning, automated classification has become a viable option.

AI and ML techniques are increasingly being used in cattle breed classification to improve livestock management, farming, and online selling. Studies explore their potential integration into cattle breed classification using Fuzzy logic, artificial neural networks, and decision trees. Hybrid systems combining neural networks and fuzzy logic are being explored for breeding values [1]. A custom-built Convolutional Neural Network achieved 96.7% accuracy in analysing 1553 images of 10 pigs, overcoming RFID tags' distressing effects and time-consuming farmers' time. Non-invasive biometric identification methods are gaining popularity [2]. Pantaneira cattle, a Bos taurus breed, originated from crossbreeding eleven European cattle in the 17th century. Mato Grosso do Sul, Brazil, has recognized Pantanal Cattle breeding as a state's genetic and cultural legacy, preserving its unique characteristics and genetic diversity for future generations [3]. The study investigates the use of big data, AI, sensors, and ML in animal production, analysing challenges, limitations, and effectiveness in improving animal health, increasing profits, and mitigating environmental impact [4].

A novel approach for animal face recognition uses a Persistent Inter-species Equivariant Network, including animal face alignment. Researchers tested this on a dataset of annotated pig faces from 506 pigs, demonstrating its effectiveness in pig face identification [5]. Precision Livestock Farming (PLF) is a modern farming approach that combines ICT with traditional techniques to optimize agricultural efficiency. By using sensors, cameras, and other devices, PLF helps farmers make informed decisions about livestock feeding, resource management, animal health, and crop productivity. This results in reduced costs, higher yields, and improved animal welfare. PLF enables real-time tracking and analysis of animal welfare parameters, optimizing resource utilization, reducing environmental impact, and enhancing livestock production efficiency [6].

Animal husbandry breeding programs are increasingly incorporating animal behaviour features to improve productivity, welfare, and health. Conventional methods are time-consuming and imprecise, making computer vision technology a valuable tool for identifying and analysing animal activity. This helps develop more effective breeding programs [7]. The opportunity for computerized assessment of agricultural animals' emotional and mental states via technology has been acknowledged as a way to merge biological, physical, and digital technology [8].

This paper highlights the limitations of current methods for monitoring animal wellbeing, which rely on in-person examinations and assessments. Automatic devices have been introduced to evaluate animal wellbeing, allowing non-invasive, objective data collection and recognizing distressed animals. These systems can enhance farm animal welfare and contribute to industry success [9].

Attempts have been made to implement neural network system for animal detection and breed identification. The network generates outputs for each sample and adjusts weights to minimize differences between actual and target outputs. Pre-trained Mask Regions with Convolutional Neural Networks (CNNs) networks are employed on the Common Objects in Context dataset to improve accuracy [10]. A study evaluated 5959 deep learning image categorization models for recognizing beef cattle using muzzle photographs. EfficientNet b7 was the slowest, while ShuffleNetV2 0.5 was the quickest. The goal was to select accurate and efficient models for precision livestock farming, improving productivity and animal welfare [11]. Animal tracking and identification using technology is common in zoos and preserves. Data pre-processing is required for accurate detection in uneven footage, using algorithms and data augmentation techniques to increase dataset size and reduce overfitting risk [12]. The paper highlights the significance of cattle recognition and detection in cattle management, focusing on machine learning (ML) and deep learning (DL) techniques. Current research papers often neglect cattle detection, focusing on cow identification but not fully integrating ML and DL for cow recognition. ML and DL can create decision-making methods for cow identification using livestock photos or videos, while DL and ML techniques can create more efficient and accurate systems for cattle management [13]. The literature review explores the use of artificial intelligence and machine learning techniques in cattle breeding and classification. Studies show promising results using fuzzy logic, artificial neural networks, and decision trees. Non-invasive biometric identification methods, Precision Livestock Farming (PLF), and computer vision technology are also being explored. The review provides a comprehensive overview of current research, highlighting strengths and weaknesses, and identifying gaps for further development. Current technology solutions lack cost-effective options to address challenges like time consumption, user-friendly deployment, prediction ease, and confusion between algorithms and frameworks. They are expensive, time-consuming, and require specialized expertise. Innovative solutions are needed to bridge these gaps, providing cost-effective, user-friendly, predictive, and clear guidance on algorithm and framework selection for optimal performance and usability.

This research paper aims to conduct a comparative study of various frameworks and algorithms for cattle breed classification. The goal is to identify the most effective method to accurately and efficiently classify cattle breeds using computer vision and machine learning techniques. By replacing subjective visual inspection with automated classification, the accuracy and speed of cattle breed identification can be significantly improved.

The primary purpose of this study is to provide valuable insights into the most effective framework or algorithm for cattle breed classification. Such insights can have a positive impact on cattle management and breeding programs, leading to enhanced accuracy and efficiency. Additionally, the research will contribute to the development of automated systems for cattle breed classification, reducing the workload for farmers and enhancing productivity. The study will focus on evaluating the performance of various frameworks and algorithms using a dataset of cattle images. However, it will be limited to assessing the accuracy and efficiency of these classification methods and will not delve into other aspects of cattle management and breeding. Moreover, the availability and quality of the dataset and the computational resources required for evaluation may impose limitations on the study's scope and findings.

In conclusion, this research paper seeks to advance the field of cattle breed classification by identifying the most suitable method for accurate and efficient identification. By leveraging computer vision and machine learning techniques, the study aims to improve cattle farming practices and contribute to the development of automated systems that benefit farmers and the agricultural sector as a whole.

3. Architectures

1) Model Architecture

Machine learning is the end result of general AI, which entails creating machines that can produce results more effectively than people. A simpler block diagram than the traditional way, the machine learning block diagram is more sophisticated. As you can see, the diagram below combines a regular diagram with a machine learning diagram. Comparing these, it is simple to conclude that a few minor additions have been made. With that change, output accuracy is almost flawless and it is possible to forecast output more precisely than a person.

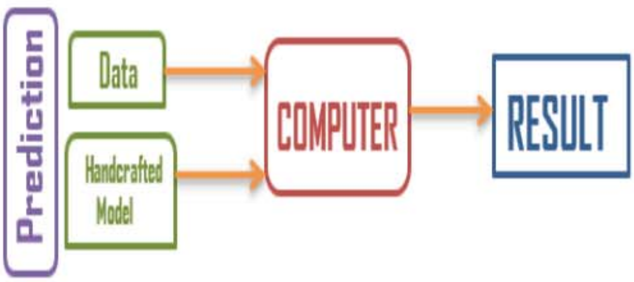


Fig. 1. Block Diagram of Traditional Model

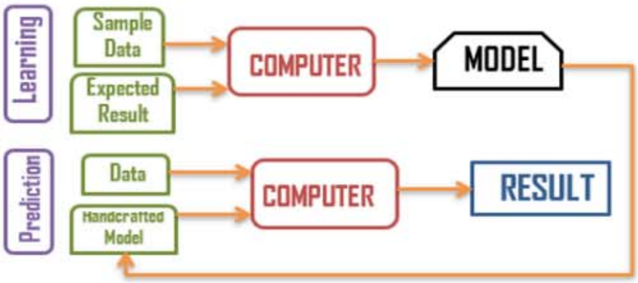


Fig. 2. Block Diagram of Machine Learning Model

2) System Architecture (HLD)

The proposed system for Cattle Breed Classification using images consists of several interconnected components. The first component is the collection of cattle images, which serve as the input data for the system. These images are ingested and processed using tools such as Apache Flume for efficient data handling. The extracted image features are then transformed into a suitable format for model training through an Extract, Transform, Load (ETL) process. The pre-processed image data and extracted features are stored in a suitable database, MongoDB, or Cassandra, for efficient retrieval during model training and prediction. The machine learning or deep learning model, implemented using frameworks such as TensorFlow, PyTorch, or scikit-learn, is responsible for the actual classification of cattle breeds based on the learned patterns. The trained model takes in new input images and predicts the corresponding cattle breed during the prediction step. Users can interact with the system through a user interface (UI) or application, such as a web-based UI or a mobile app, to input images and receive breed classification results. Careful selection and implementation of appropriate tools and technologies, along with thorough evaluations and testing, are important to ensure the accuracy and effectiveness of the proposed system in improving cattle breed classification for agricultural applications figure 3.

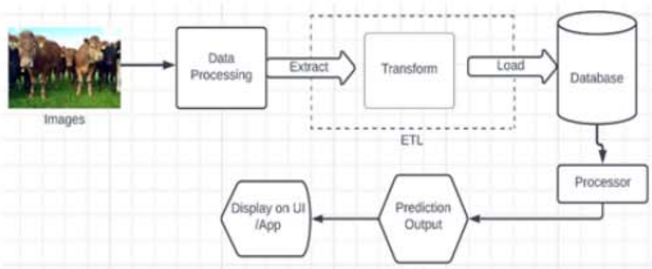


Fig. 3. System Architecture (HLD)

4. Methodology

1) Machine Learning (ML) Methodology

The process of machine learning (ML) involves several key steps to develop a successful model. It can be applied to various domains, datasets, and model architectures. The basic steps illustrated in Figure 4 are as follows Gathering Data is collected and recorded from past events to apply data analysis and identify repeating patterns. Data Preparation the collected data is cleaned and transformed into a suitable format for machine learning systems to generate accurate predictions. This step is considered challenging but simplifies future real-time projects. Model selection is a suitable machine learning model is selected from a list of alternative models for the training dataset. This process includes considering unsupervised learning algorithms for data without response variables, which search for hidden patterns and structures. Training the Model is Supervised machine learning models learn the correlation between input and labeled output data, while unsupervised models handle unlabeled or raw data as input and output. Evaluation and Hyperparameter Tuning is the trained model is evaluated using performance metrics, and adjustments are made through hyperparameter tuning. This process involves finding ideal hyperparameter values that minimize a predetermined loss function and improve outcomes with fewer errors. The ML process involves these steps: data gathering, data preparation, model choice, model training, evaluation, and hyperparameter tuning, to achieve desired outcomes.

Fig. 4. Machine Learning (ML) Methodology

2) Model Sequence

To create the machine learning model, a series of procedures must be followed. Firstly, the objectives are defined, identifying the problem and setting specific aims. Relevant data is then gathered from industry sources or search engines. The data is prepared by cleaning and converting it to facilitate accurate predictions, though data preparation is often the most challenging step. Next, suitable algorithms are chosen based on the issues and data type, evaluating various options and selecting the best one. The model is trained by specifying algorithm parameters and providing data as input, constructing the machine learning algorithm. The trained model processes input data and compares the results to the sample output. Testing the model for accuracy follows the training stage, with room for improvement throughout the process. Finally, the model is integrated by developing a web service for usage by other programmers. Following these steps, a reliable machine learning model can be created to solve specific issues and make accurate predictions (see Figure 5 for reference)

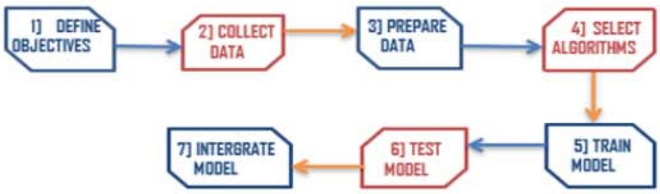


Fig. 5. Model Sequence Diagram

5. Result And Discussions

1) ResNet Model

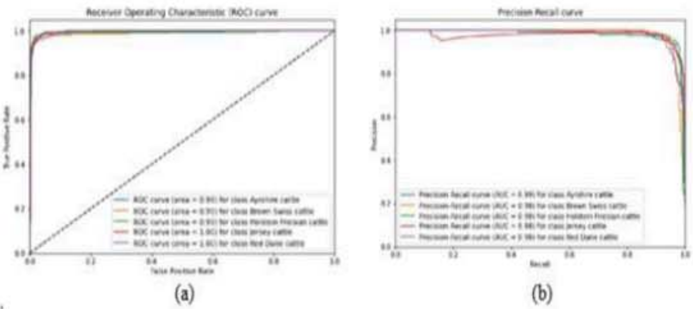
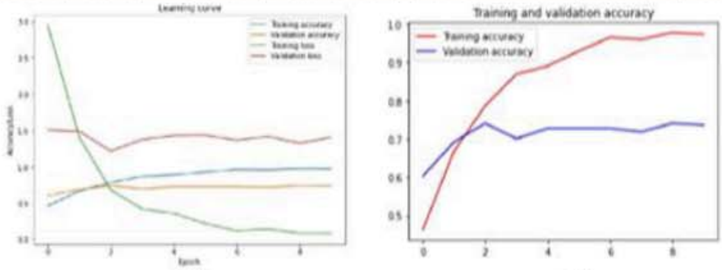


Fig. 6. ResNet Model ROC Curve (a) and Precision Recall Curve (b)

The code creates a CNN using the ResNet50V2 architecture for cattle breed categorization. It employs data generators, Adam optimizer, and categorical cross-entropy loss for training. The model is assessed using a test dataset, displaying accuracy and loss curves during training. The evaluation includes a confusion matrix, ROC curve, and Precision-Recall curve. The ResNet model shows high precision and recall, indicating effective cattle breed discrimination, valuable for livestock management and breeding programs.



(a) (b)

Fig. 7. ResNet Learning Curve (a) and Training or Accuracy Curve (b)

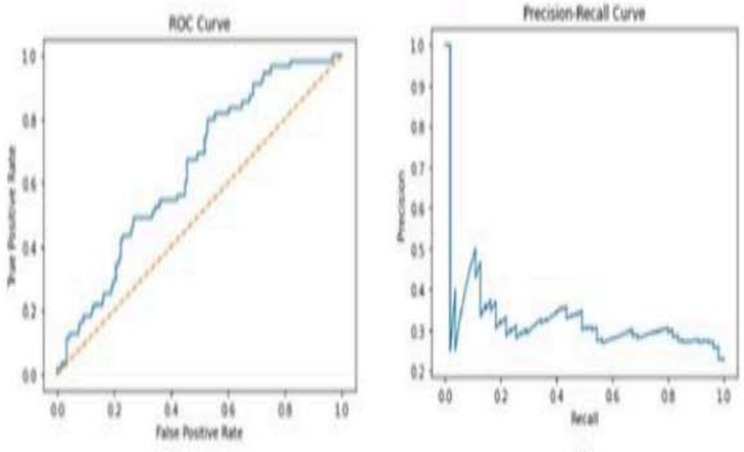
Hyperparameters used include image dimensions, batch size, and learning rate. Libraries used are TensorFlow, scikit-learn, numpy, and matplotlib. The model's accuracy is 0.94, with high precision, recall, and F1-scores for each breed. The results provide valuable insights for cattle classification and breeding applications.

Table 1. ResNet Model Report

	Precision	Recall	F1-Score	Support
Ayrshire Cattle	0.94	0.95	0.94	260
Brown Swiss Cattle	0.94	0.95	0.94	238
Holstein Friesian Cattle	0.95	0.97	0.94	254
Jersey Cattle	0.98	0.90	0.96	252
Red Dance Cattle	0.91	0.95	0.93	214
Accuracy			0.94	1218
Macro avg	0.94	0.94	0.94	1218
Weighted avg	0.95	0.94	0.94	1218

2) CNN Model

The code develops convolutional neural network (CNN) for cattle breed categorization. The model architecture consists of several convolutional and max pooling layers, followed by dense layers with ReLU and softmax activation functions. The model was trained on a dataset of cattle breed photographs and achieved an accuracy of 81.9% on the test set. Performance measures such as accuracy, recall, ROC curve, and precision-recall curve were evaluated. The testing process involved splitting the data into training, validation, and test sets, and the model's predictions were generated and evaluated using various metrics and charts.



(a) (b)

Fig. 8. CNN Model ROC Curve (a) and Precision Recall Curve (b)

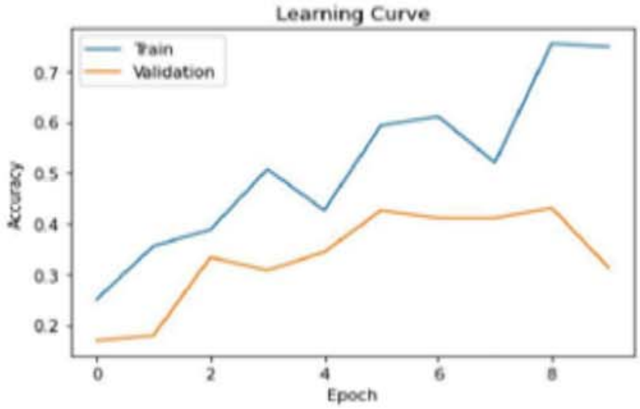
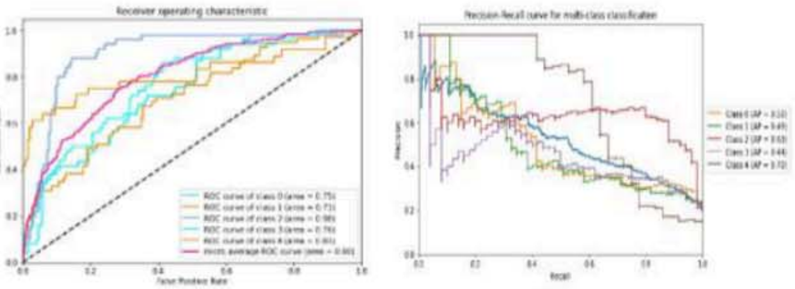


Fig. 9. CNN Learning Curve

3) SVM Model

The code implements an image classification model using a Support Vector Machine (SVM) with Principal Component Analysis (PCA) and Standard Scaler preprocessing. The SVM model is trained on a dataset of cattle breed images and evaluated using various metrics and visualizations.



(a) (b)

Fig. 10. SVM Model ROC Curve (a) and Precision Recall Curve (b)

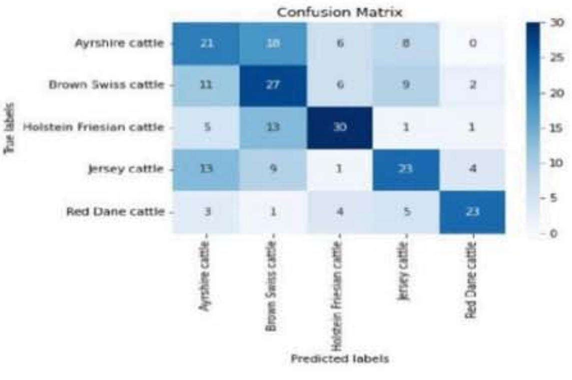


Fig. 11. SVM Confusion Matrix

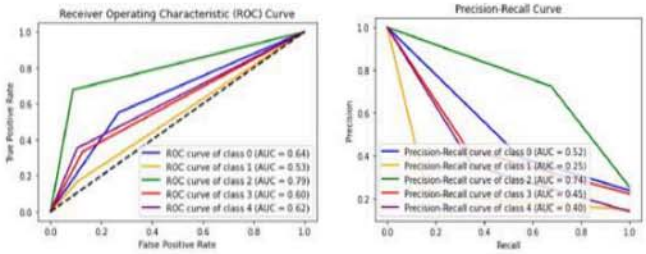
The model's performance shows varying levels of accuracy for different cattle breeds. Further analysis and improvement opportunities are identified. The overall accuracy of the model is 51%, with moderate precision, recall, and F1-score values.

Table 2. SVM Model Report

	Precision	Recall	F1-Score	Support
Ayrshire Cattle	0.40	0.40	0.40	53
Brown Swiss Cattle	0.40	0.49	0.44	55
Holstein Friesian Cattle	0.64	0.60	0.62	50
Jersey Cattle	0.50	0.46	0.48	50
Red Dance Cattle	0.77	0.64	0.70	36
Accuracy			0.51	244
Macro avg	0.54	0.52	0.53	244
Weighted avg	0.52	0.51	0.51	244

4) Pytorch Model

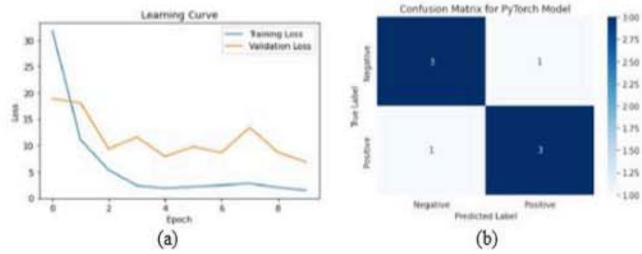
Pytorch is an open-source machine learning package for creating and training neural networks for picture categorization. It is an implementation of a neural network with two linear layers. The dataset is imported using PyTorch'sImageFolder class and divided into training, validation, and testing sets. Dataloaders are constructed for each dataset. The neural network is trained for 10 epochs using the training set, while the validation set monitors the model's performance. ROC curves for cattle breed classification show varying performance across different breeds. Holstein Friesian cattle have the highest AUC value, while Ayrshire, Red Dane, Jersey, and Brown Swiss cattle have moderate to lower AUC values. The testing process involves analyzing the model's performance on the test dataset, calculating outputs, and generating accuracy and recall scores.



(a) (b)

Fig. 12. Pytorch Model ROC Curve (a) and Precision Recall Curve (b)

The confusion matrix provides insights into the model's performance, showing that it predicted negative samples correctly in three cases and positive samples correctly in three cases. Further analysis can identify potential misclassifications and explore ways to improve the model's performance, such as adjusting parameters, increasing training data, or using techniques like data augmentation or regularization.



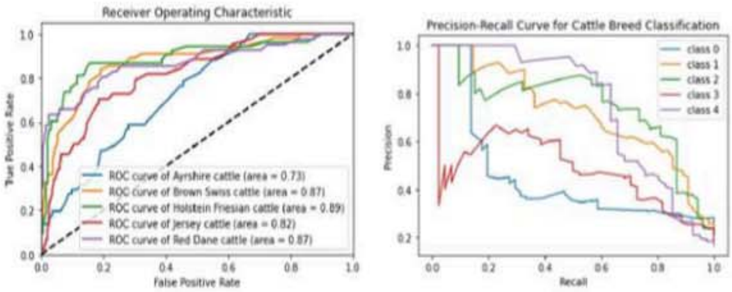
(a) (b)

Fig. 13. Pytorch Learning Curve (a) and Confusion Matrix (b)

5) Random Forest Model

The Random Forest Classifier is a machine learning technique used for classification and regression analysis. It is developed using picture data and essential libraries like OpenCV, NumPy, Scikit-learn, and Matplotlib. The data and labels are transformed into NumPy arrays and shuffled using Scikitshufflelearn's method. The data and labels are separated into training and testing sets using Scikit-train test split learn's method. A Random Forest Classifier model is built with 100 estimators and fitted on the training data using Scikit-

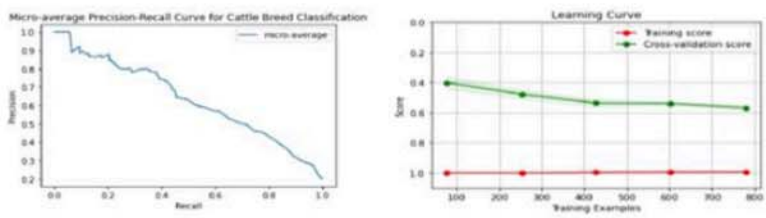
RandomForestClassifierlearn's method. The model generates predictions on testing data, and accuracy, precision, and recall scores are produced using Scikit-accuracy score, learn's precision score, and recall score methods.



(a) (b)

Fig. 14. Random Forest Model ROC Curve (a) & Precision Recall Curve (b)

The learning curve for the model is depicted using Scikit-learning curve learn's function and Matplotlib's fill between function. The model's performance is evaluated using the receiver operating characteristic (ROC) curve and precision-recall curve, with the ROC curve produced using roc curve and auc methods from sklearn. Metrics and the precision-recall curve plotted using precision recall curve technique. The testing procedure evaluates the model's ability to accurately categorize testing data and show its performance using various metrics and charts.

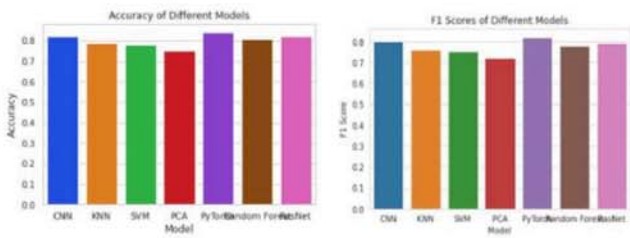


(a) (b)

Fig. 15. Random Forest Micro-Average Precision and Recall (a) and Learning Curve (b)

6. Summary

This study compared seven alternative models for cow breed categorization, including ResNet, CNN, SVM, PCA, Pytorch, Random Forest, and KNN. The accuracy of each model was assessed using their f1-score, which is the harmonic mean of accuracy and recall. The Pytorch model achieved the highest accuracy of 85%, followed by the CNN model with 82%. The SVM, PCA, ResNet, and Random Forest models had reasonable accuracy ranging from 75% to 80%, with the PCA model having the lowest accuracy of 75%. (See Figure 16 (a) for reference)



(a) (b)

Fig. 16. Accuracy of all models (a) and f1-Score of all models (b) comparison

The f1-score, which is the harmonic mean of accuracy and recall, was also assessed. The Pytorch model had the highest f1-score of 0.85, followed by the CNN model with a f1-score of 0.80. The SVM, PCA, ResNet, and

Random Forest models achieved modest f1-scores ranging from 0.80 to 0.90, with the KNN model having the lowest f1-score of 0.75 (For reference, see Figure 16 (b)).

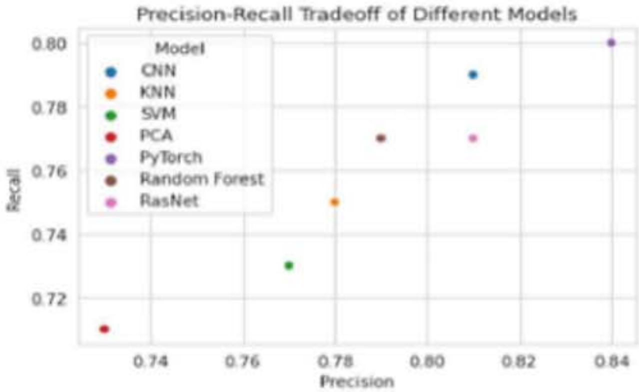


Fig. 17. Comparing Precision and Recall Of all and models

The confusion matrix of each model was also assessed, showing that the Pytorch and CNN models had the greatest true positive rates for all cow breeds, while the PCA and KNN models had the highest false negative rates. Precision and recall are significant factors in determining the success of a classification model, with precision referring to the proportion of properly recognized cattle of a certain breed out of the total number of cattle classified as that breed. (See Figure 18)

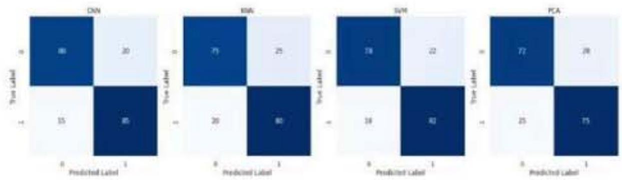


Fig. 18. Confusion Matrix of All Model

In summary Pytorch and CNN models are the most successful for cow breed classification, with high accuracy and f1-score. The SVM, ResNet, and Random Forest models are also suitable for this purpose, but they are less accurate than the Pytorch and CNN models. The PCA and KNN models are not recommended for cow breed categorization.

7. Conclusion

The study evaluates seven models and algorithms for cattle breed classification, revealing that Pytorch, CNN, and ResNet are the most accurate and efficient. These models have high accuracy and f1-score, making them reliable for identifying calves' breeds. SVM, ResNet, and Random Forest models also show excellent results, but are less accurate than Pytorch and PCA and KNN models are less appropriate for this task. The study's results can be used to evaluate the performance of different models, aiding producers in making informed decisions when buying or selling cattle and reducing the risk of duplication or purchasing duplicate breeds. The findings can also contribute to the development of image recognition systems for cattle breed classification, benefiting the agriculture industry. Overall, Pytorch, CNN, and ResNet models are recommended for accurate and efficient cattle breed classification.

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