Deep Learning Approaches for the Prediction of Goat Diseases

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Abstract. Goat farming can be said to be one of the branches of agricultural activity that is of great importance to the economy of a nation like India. The raising of livestock especially in the rural parts pays about 4% of the GDP of the country in the form of employment and food security. However, dry areas are frequently faced with a shortage of veterinarians, which creates a barrier for farmers to receive veterinary care on time. If animals are not properly supervised, the risk of goats developing complications or dying from untreated infections is very high. Apart from herding goats, most farmers don't bother to look for signs of illness in their animals, such signs include: fever and low feed intake, which means by the time some of them recognize that their goats are sick, it is often too late and they incur huge losses. Some small-scale farmers on the other hand do not vaccinate their animals enough due to the costs of vaccination without which the diseases become rampant. This study presents an application, which enables the identification of goat diseases and recommends treatment through an image-based prediction. For effective detection, the model is trained using YOLO after employing a specialized image feature extraction technique, all the while bettering test image accuracy with ResNet-50. The accuracy of the model is 82.67%. The application can offer simple medical prescriptions and instructions for disease control. Considering low-powered devices, the approach does not connect to the internet, thus making it possible to provide near-to real-time predictions assisting farmers in far-flung areas to take good care of goats and limit losses.

Keywords: Goat farming, diseases, YOLO, ResNet-50, prediction, treatment.

1 Introduction

A major contributor to the rural economy, goat farming creates jobs, food, and revenue. Because they can thrive in a variety of conditions, goats are a popular choice for livestock all around the world. In addition to offering farmers milk, meat, and dung, goats also help farmers diversify their sources of revenue and lessen their dependency on a single crop or type of farming.[1] Since goat farming may be done on a smaller scale, it is an appropriate venture for smallholder farmers who lack a large area or infrastructure**.**

Challenges in Goat farming:

- Limited Access to veterinarian Care: Farmers frequently face difficulties in obtaining fast veterinarian care in rural locations. Delays in treating sick animals may result in complications or even death[2][3].

- Disease Identification: Without professional guidance, it can be challenging to diagnose many goat diseases, which manifest signs including fever and lethargic behavior. It's possible that farmers lack the expertise to properly treat or manage illnesses.

- Cost of Vaccination: Although vaccines are essential for preventing illnesses, small-scale farmers may not be able to afford them, which could result in under-vaccination and a higher risk of illness.

Table no.1 Major Disease

		
Anthrax	CLA	CCPP
		
Ringworm	Footrot	Healthy Goat

Fig.1 Goat Diseases

Anthrax: Goats are susceptible to the bacterial illness anthrax, which is primarily observed in anthracite is the causative agent.

CLA: The bacteria Corynebacterium pseudotuberculosis is the cause of caseous lymphadenitis. Sheep can contract diseases directly from one another while confined in close quarters or indirectly through tainted shearing equipment.

CCPP: Goats and certain wild ruminant species are susceptible to a serious disease called contagious caprine pleuropneumonia (CCPP), which is brought on by the germs Mycoplasma capricolum subsp capripneumoniae (Mccp).

Ringworm: The fungus known as ringworm, or wool fungus, is typically found in the Mycosporum or Trichophyton species Ringworm usually affects the sheep and goats' faces, ears, necks, and bodies[4].

Footrot: Goats frequently contract the infectious bacterial ailment known as "footrot," which damages their hooves and causes pain and disability. Two different kinds of bacteria—Fusobacterium necrophorum and Dichelobacter nodosus—cause it.

Calculate the total money spent on one goat and determine the remaining amount as profit for a farmer

Table no.1

Feeding Costs((1-6kg Green Grass*6 per Kg)+200 supplement food *50 per kg)*365	8000
Average Labour Cost per goat	1000
Vaccination(FMD, PPR)	600
Medical	1000
Supplements(Calcium, Liver Tonic)Deworming	800
Total Breeding cost	11200
Selling price(40kg*400)	16000
Profit	**5000**

The strategy of this study for predicting goat diseases focuses on the diagnosis and treatment suggestions of diseases through image-based technology. Using ResNet-50, the model can reliably identify the presence of a variety of diseases by examining images of goats[5]. Based on the diagnosis, this system not only determines the illness but also suggests a general course of treatment. The app will not only provide treatment recommendations but also vital information regarding vaccines that assist farmers in protecting their goats from common diseases by helping them comprehend the essential vaccination schedules. By offering easily available and real-time disease prediction, this strategy seeks to empower farmers by facilitating early vaccination and treatment to enhance the general health of their herd.

2 Literature Survey

Kasian Myagila et al. presents a model that uses observable symptoms to categorize PPR disease in sheep and goats. They collected data in Tanzania. In this work, four machine learning algorithms—Decision Tree, K-nearest neighbor, Support Vector Classifier, and Logistic Regression—have been used to develop and assess models.

The accuracy of the models' classification was used to assess how well they performed. According to the results, the algorithms for Support Vector Machine and Logistic Regression both scored the highest—79% on sampled data and 81% on unsampled data—indicating their efficacy in predicting PPR. The study's limitations include unbalanced data, limited algorithms, and insufficient performance measures, necessitating future research to enhance machine learning models' resilience and suitability for PPR disease prediction [6].

Dario Augusto Borges Oliveira et al. This paper traces the development of computer vision technologies in the field of livestock management, emphasizing the move from conventional approaches to sophisticated deep learning techniques that have improved the efficiency and accuracy of livestock monitoring. It examines several deep learning techniques used for tasks involving livestock, with an emphasis on Convolutional Neural Networks (CNNs), which are particularly good at image recognition and classification pertinent to the health and behaviour monitoring of livestock. These models are trained using a thorough procedure that includes data splitting for training, validation, and testing as well as performance evaluation using metrics like accuracy, precision, and recall. [7].

Ahmad Ali AlZubi By applying deep learning and machine learning approaches, the author offers a model for predicting animal diseases. The author talks about various models, one of which being Convolutional Neural Networks (CNN), which has a high diagnostic accuracy of 96.9% for animal diseases. There was a 6.8% and 90% specificity classification error in the PLS-DA model. Compared to PLS-DA, the ANN model's classification error was 8.9%, which was somewhat larger. With a specificity of 100%, all negative instances were accurately identified. The CNN model, however, displayed the best overall accuracy. [8].

M.Thenmozi et.al.The authors analyze sheep video footage using deep learning techniques, such as a sequential model and the Single Shot Multibox Detector (SSD) algorithm. They recognize certain behaviors, including as aggressiveness, redness, skinniness, and foraging. Compared to the YOLO algorithm, the SSD algorithm improves prediction rates by 3 to 6% and produces a bounding box and confidence percentage. The paper addresses the challenges related to the complexity of behavioral data by combining spatial and temporal features. [9].

Machuve, D. et.al. Deep learning techniques were used in this work to diagnose diseases of chicken, including fowl pox, Newcastle disease, avian influenza, Marek's disease, and coccidiosis. For image classification tasks, it makes use of convolutional neural networks or CNNs. The model's recall, accuracy, precision, and F1-score are its performance metrics. In the trials involving the five models—baseline CNN, VGG16, InceptionV3, MobileNetV2, and Exception—he employed accuracy as one of the performance indicators. With test data, the baseline model had the lowest accuracy of 83.06% while training the models without fine-tuning. At 94.79%, the InceptionV3 had the highest accuracy. [10].

Mizanu Zelalem Degu et.al. An automated approach for identifying and categorizing chicken diseases from fecal photographs was established in this work using a mobile device. Creating a collection of images of chicken feces was the initial stage. 10,500 images in all were gathered from the Zenodo open database. Using the YOLO-V3 object identification technique, the system extracted ROIs. Then, it trained the ROIs using the ResNet50 architecture to categorize the segmented images into four categories: New Castle Disease, Coccidiosis, Salmonella, and Healthy. The system's 98.7% classification accuracy shows how effective it is at managing and detecting diseases. An interface for a mobile app was created for use in real life. [11].

Ravikiran Keshavamurthy et.al. The paper discusses various methods used in infectious disease prediction, including Decision Trees, Support Vector Machines (SVM), Random Forests, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs). It also discusses the integration of ML and Deep Learning techniques to create hybrid models. Despite these challenges, many models have achieved high accuracy rates. Machine learning and deep learning models have shown high accuracy rates in predicting infectious disease outbreaks, with some studies exceeding 90%, demonstrating their potential for effective public health responses. [12].

M.F. Ismail Kamil's et.al.To predict sheep breed lineage and manage disease data, the study included both qualitative and quantitative data collection techniques. The study employed the Feedforward Artificial Neural Network (FANN) to identify the internal and external elements that impact the continuity of sheep breed lineage. By improving the handling of sheep breed and disease data, the model hopes to enhance health monitoring and breeding procedures. These interviews were analyzed in order to find important traits, such as average daily gain (ADG), body condition score (BCS), and particular breed characteristics, that may be useful in determining breed ancestry. The challenges of merging genetic and health data into a single model is another issue that is covered in the study. [13].

Ahmad Ali Alzubi The study uses images from the agricultural landscape to identify cattle skin conditions. Convolutional Neural Networks (CNN) are used to classify LSD (infected)and non-LSD(non-infected) skin. The CNN model is trained over 50 epochs to identify features. Evaluation metrics include accuracy, loss, and confusion matrix. Future work includes addressing dataset limitations, refining model parameters, reducing image noise, exploring feature extraction methods, and investigating additional animal skin conditions. The CNN-based model achieved an accuracy of 86.54%. Limitations include a small and homogeneous dataset, which affects generalization across breeds and their conditions, and challenges related to real-world deployment due to inconsistent image quality. [14].

Ratan Raj Kumar Kola et al.The paper presents a method for detecting and predicting tumour's in livestock using advanced technology. It uses a deep neural network, specifically Keras and TensorFlow frameworks, to analyze MRI images of livestock brains. A convolutional neural network is used for initial tumor prediction. A pre-processing step is performed to isolate noise and artifacts. A computer-aided detection system is proposed, providing timely information about livestock health status. The system integrates with IoT to communicate detection results directly to cattle farmers, bridging the geographical gap between sick animals and veterinary services.There are still key gaps that fall under the development of lightweight, computation friendly models and cheaper alternatives to MRI in imaging. [15].

3 Methodology

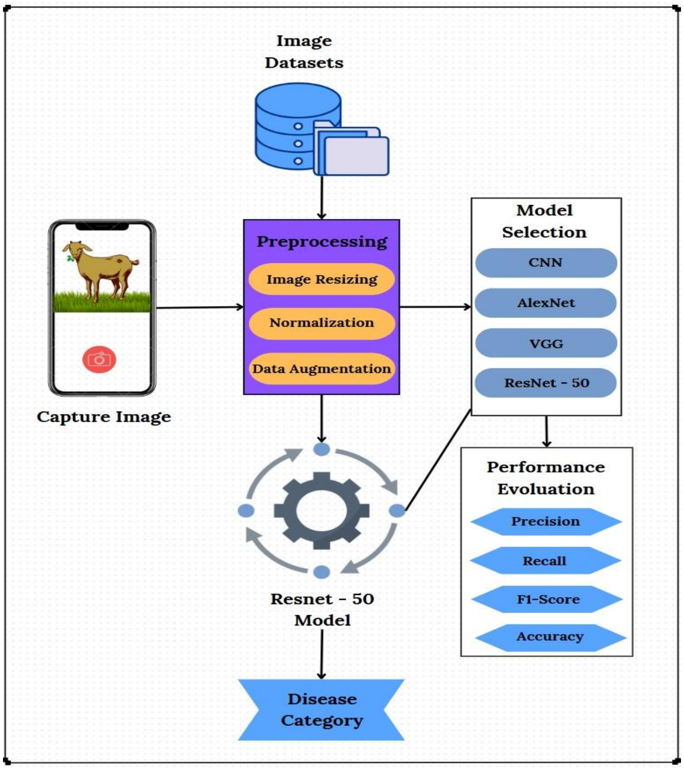

Fig.2 Architecture diagram

3.1 Dataset Preparation:-

To collect a comprehensive dataset of goat farms suffering from various diseases, gather images from various sources such as veterinary clinics, research facilities, and publicly accessible datasets. Include diagnoses, symptoms, and relevant metadata such as age and breed. Collect images in common file types like JPEG or PNG, with constant resolution.

3.2 Preprocessing:-

Image cleaning involves noise reduction and contrast adjustment to remove artifacts and improve image quality. Normalization and resizing ensure consistency. Data is divided into training, validation, and testing sets, and a ResNet-50 is selected for image categorization. The model's robustness is enhanced through various methods, including rotation, flipping, zooming, cropping, brightness adjustment, and shearing. Libraries like PyTorch, TensorFlow, or Keras are used for augmentation during training.

3.3Model Selection and Training:-

This paper presents a model trained by Yolo and ResNet-50 deep learning algorithms. Yolo is popular for object detection algorithms, and it is efficient and fast for feature extraction. These characteristics are mapped to distinct illness categories by the ResNet model through training. For instance, ResNet can determine whether a goat has footrot or any other ailment based on features mapped from an infected hoof. YOLO is used for feature extraction for the eye, mouth, skin, foot, etc., and Resnet is used to predict disease.

3.4 Evaluation Metrics:-

- Accuracy: percentage of accurate prediction.
- Precision: percentage of all optimistic predictions that were actually positive.
- Recall (sensitivity): percentage of actual positives divided by the number of true positive predictions.
- F1-Score: The precision and recall harmonic mean[16].

To ensure the model generalizes well, evaluate it on validation and test sets.

3.5 Algorithm Description:

CNN: Convolutional neural networks (CNNs) are a specific kind of deep learning model that are used for tasks related to image recognition and classification. It works by using a number of layers that recognize patterns in the pixel values of images[17].

- Convolutional Layers: These layers apply filters on the images that are provided to identify characteristics that are essential to diagnosing illnesses, like edges, textures, and colors.
- Pooling Layers: By minimizing the spatial dimensions of the images, these layers simplify computation and aid in concentrating attention on the most important aspects[18].
- Fully Connected Layers: These layers group the retrieved features and assign the image to a disease category (or state of health).

Alexnet: One of the first deep CNN models to make significant progress in picture categorization was AlexNet. It is frequently credited for sparking the deep learning revolution in computer vision, by winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC).

- Activation function: After every layer, the activation function was changed to ReLU (Rectified Linear Unit), which accelerated training and added non-linearity. When compared to more conventional activation functions like sigmoid or tanh, ReLU activation helps reduce vanishing gradient issues.
- Pooling: To minimize the spatial dimensions, use max pooling layers.
- Dropout: During training, the output of certain neurons is randomly reduced to zero in order to reduce overfitting.

VGG-16: The Visual Geometry Group (VGG) created and released VGG16. It acquired notoriety for employing tiny convolutional filters, having a deep architecture, and performing well on the ImageNet dataset[19].

- 16 layers total—3 fully linked layers and 13 convolutional layers. Convolutional Filters: These filters help extract fine-grained features by using tiny 3x3 filters throughout the network.
- Pooling: To minimize spatial dimensions, perform max pooling after a few convolutional layers.
- Three fully connected layers are used at the end to get the final categorization.

ResNet-50: ResNet-50 is a member of the Residual Networks family, which debuted the idea of residual learning. ResNet used shortcut connections to solve several problems with deeper networks, such as gradients that disappeared and went on to win the ILSVRC competition.

- 50 layers total:1 max-pooling layer, 1 average-pooling layer, and 48 convolutional layers. It is made up of residual blocks with three convolutional layers in each[20]
- 8 layers: three fully linked layers and five convolutional layers.
- Bottleneck Blocks: These blocks use a bottleneck design (1*1, 3 * 3, and 1 * 1 convolutions) to Skip connections, sometimes referred to as shortcuts, introduced by residual learning. These connections skip over some layers and send information straight to deeper layers. This makes it possible to create much deeper networks and helps avoid the vanishing gradient issue.

4 Result and Description

I. Experimental setup :

Google Collab played a critical role in the development and experimentation of the goat disease prediction model by providing a free, accessible, and powerful environment. Its cloud-based nature, support for essential libraries, and ability to handle CPU-based testing made it an ideal platform for simulating real-world farming conditions, where computational resources may be limited**.**

II. Matrix Representation :

Table 2 Performance Metrics Per Category

Category	Precision	Recall	F1-score
Anthrax	**0.820**	**0.800**	**0.810**
CLA	**0.814**	**0.840**	**0.827**
CCPP	**0.827**	**0.846**	**0.837**
Ringworm	**0.806**	**0.800**	**0.803**
Footrot	**0.823**	**0.816**	**0.819**
Healthy Goat	**0.873**	**0.858**	**0.866**

Table no 2 describes Per-category precision, recall, and f1-score values for every disease are shown in the table. Ringworm has the lowest precision (0.806), recall (0.800), and f1-score (0.803), whereas the healthy goat group has the best precision (0.873), recall (0.858), and f1-score (0.866). All categories show consistent, if somewhat different, performance. Lower precision for diseases like Anthrax and Ringworm resulted from high false positives, where symptoms overlapped with conditions like CLA or Footrot. Similarly, lower recall occurred when subtle or ambiguous symptoms (e.g., early stages of Footrot or Ringworm) led to misclassifications.

Table 3.Confusion Matrix

True/pred	Anthrax	CLA	CCPP	Ringworm	Footrot	Healthy Goat	Total
Anthrax	100	10	5	5	3	2	125
CLA	8	105	4	3	3	2	125
CCPP	5	4	110	6	3	2	125
Ringworm	4	5	6	100	7	3	125
Footrot	3	3	5	6	102	6	125
Healthy Goat	2	2	3	4	6	103	125
Total	122	129	133	124	124	118	750

Table no 3 states The confusion matrix for all categories, totaling 750 samples, is displayed in this table. The ResNet classification model's correctly categorized samples are displayed by the diagonal value. There are 110 correctly identified samples in the CCPP, which is the most. Misclassifications occur in a few different categories.

Table 4 precision matrix

Algorithm	**Accuracy**	**Precision**	**F1 score**	**Recall**
CNN	**79.34**	**0.78**	**0.785**	**0.79**
Alex Net	**81.89**	**0.81**	**0.815**	**0.82**
ResNet-50	**82.67**	**0.827**	**0.830**	**0.834**

Table no 4 shows the maximum accuracy of 82.67, ResNet-50 is the best architecture for image classification applications since it combines exceptional depth, efficiency, and accuracy. It is more scalable and adaptive to challenging image classification tasks due to its innovative residual learning technique, which enables it to train deeper networks without the typical drawbacks of disappearing gradients.

5 Conclusion

The introduction of a goat disease prediction application is a major step forward in livestock health management. The application makes utilize of Convolutional Neural Networks. And deep learning which provide efficient platforms to assist in diagnosing illnesses and managing environmental constraints. Through this application, the diagnosis can identify goat health issues by studying previously diagnosed cases of vulnerable bacterial, fungal, and parasitic diseases. As the application heavily relies on resnet-50 which specializes in visual content understanding and image categorizing using linked graphics processing units, it is able to make accurate estimations based on images provided by end users. For livestock health management in particular, the app helps in preventing losses in case of an underlying epidemic by enabling early detection of diseases. Additionally, the innovation showcases the fusion of modern technology industries with traditional farming practices.

Potential productivity can be derived from the application in its present form. As for now, it can be said that there exists a scope for further improvement of this work. These include the following possibilities: Enhancement of the dataset: Compiling and use of extensive dataset in order to increase the level of accuracy and broadness of the model. Adjustment Multi Species: Altering provisions of the system in order to facilitate disease forecasting in different types of livestock as part of multi species adjustment strategy. Integration of IoT: Modelling practices with the use of a remote

IoT enabled sensors data on the environmental factors like temperatures, humidity and feed values for a more thorough and detailed management of diseases.

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