CATTLE EXTERNAL DISEASE CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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APPROVAL

This Project/internship titled **“Cattle External Disease Classification using Deep Learning Techniques”**, submitted by **Md. Rony, ID No: 181-15-10527, and Riad, ID No: 181-15-10969, and Dola Barai, ID No: 181-15-10724** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 02 January, 2022.

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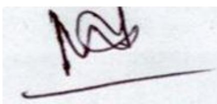

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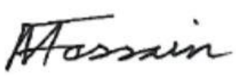

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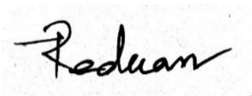

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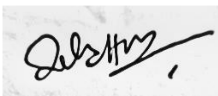

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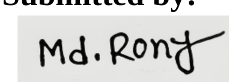

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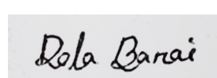

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ABSTRACT

External cattle disorders such as Foot and Mouth Disease (FMD), Lumpy Skin Disease (LSD), and Infectious Bovine Keratoconjunctivitis (IBK) are among the most common in the sub-continent. Early detection is critical for disease control. The most widely utilized architecture in the state-of-the-art of image processing and computer vision is the typical convolutional neural network. No other method for detecting cattle diseases in a husbandry farm has been implemented, leveraging deep learning techniques to our knowledge. This suggested model uses different CNN architectures such as traditional deep CNN, Inception-V3, and VGG-16 in the area of deep learning to identify the most prevalent external illnesses at an early stage. The document details every step involved in conducting the illness detection model, from data collection through procedure and result. The suggested approach is successful, obtaining findings with a 95% accuracy rate, which may help decrease human error during the classification and aid veterinarians and livestock producers in recognizing diseases.

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CHAPTER 1

Introduction

1.1 Introduction

Cattle disease is a significant impediment to domestic animals worldwide, resulting in a high mortality rate. To reduce fatality rates, it is established that early disease recognition is quite useful. The conventional approaches are inefficient and prone to error because they rely on veterinarian's experience and naked eyes for recognition. Occasionally, the disease diagnosis is incorrect, and the appropriate treatment is recommended. This results in cattle mortality and has a significant influence on a country's livestock industry's economic growth. As a result, very efficient and automated methods for recognizing the cells of cattle lesions are required [1]. Among the various diseases that cattle can contract include Anthrax, Bovine Viral Diarrhea (BVD), TB (Bovine Tuberculosis), Foot and Mouth Disease (FMD), Lumpy Skin Disease (LSD), Infectious Bovine Keratoconjunctivitis, and others. This article discusses the importance of early diagnosis in three of the most common and dangerous external lesion disorders like FMD, LSD, and IBK [2].

According to a publication published on October 16, 2018, FMD affects 55.13 million domestic animals in Bangladesh [3]. On July 10, 2017, another report stated that over 100 cows died of FMD and over 1,500 were infected in Joypurhat's Kalai Upazila [4]. Aphthovirus causes an epitheliotropic, transboundary, and highly contagious viral disease that affects cattle, buffalo, sheep, goats, and wild animals all over the world [5]. It shows the lesions on the tongue, lips, and foot. Saliva is ejected from the mouth, and pus and blood are ejected from the feet. On January 11, 2020, it was discovered that out of 52,81,068 cattle in Chittagong, 2,62,535 livestock with 9,993 calves had been infected with LSD, resulting in the death of 26 battles with 11 calves and the abortion of 43 infected cattle. The LSDV virus causes a contagious, transboundary viral illness in buffalo and cattle (Lumpy Skin Disease Virus). As a result, infected cattle's wound skin takes on a nodular appearance with a radius of 5-25 mm [6].

Pinkeye, also known as Infectious Bovine Keratoconjunctivitis (IBK), is a highly contagious ocular disease that mostly affects calves. *Moraxella Bovis* can cause infection, and in severe cases, the infection might result in vision loss. The period is usually 2-3 days, with a small low-opacity area appearing on the membrane every 2 days, and membrane lesions are usually located in the center of the eye [7]. Computer vision is now extensively used in the breeding of cattle and the protection of livestock. ANN (Artificial Neural Networks) and CNN are two of the most common early detection techniques for diagnosing external cattle diseases [8]. This study proposes using CNN (Convolutional Neural Network) techniques and two common architectures, VGG-16 and Inception-V3, to detect external cattle diseases. CNN is a feed-forwarding ANN with features such as pool operation, generalization, regularization, and territorial connection that make it possible to reduce network complicity practically [9]. VGG-16 is a CNN architecture with sixteen convolution layers and is a Keras library pre-trained model [10]. Inception-V3 is a CNN architecture that was developed as a GoogleNet plugin to aid in data exploration and object detection [11]. Cattle are classified scientifically as shown in Table 1.1.

TABLE 1.1: CATTLE SCIENTIFIC CLASSIFICATION CHART

Scientific Classification	
Kingdom	Animalia
Phylum	Chordata
Class	Mammalia
Order	Artiodactyla
Family	Bovidae
Genus	Bos
Species	Taurus or indicus

The sequence of this procedure is presented below:

a) The traditional CNN algorithms detect three types of cattle external diseases with the least amount of error, detecting FMD, LSD, and IBK images.
b) Automated systems for detecting external and common cattle diseases will assist husbandry producers in reducing the physically demanding observing job on a large farm.

1.2 Motivation

The economic situation of South Asian farmers is much worse than in other countries. Their livelihood depends entirely on agriculture. Like other countries, a large number of farmers keep cattle in Bangladesh. Most of the families in the village make a living by selling cow's milk. Cattle disease is a big threat to farmers. Some diseases cause the infected cows to become very weak, lose their ability to reproduce and give milk. Sometimes the disease can lead to the death of the cows. As a result, farmers face economic losses and make their lives difficult. If they can detect cattle diseases at an early stage, they can avoid economic losses. It will also help improve their financial situation. Now is the time of the technological revolution. In today's digital age, agriculture has been connected with the latest technology and farmers can use the latest technology in their smartphones, which is very important. However, there is still a lack of knowledge to train farmers in issues like disease detection and management. This is why we hope to establish a system that will be beneficial for farmers who do not understand animal diseases. The system will focus on creating animal disease management services with the help of smartphones [2].

1.3 Objectives

- As we mentioned earlier, the work done in this area so far has not been good. Also, to our knowledge, no one uses deep learning algorithms.

- This is why we are interested in cattle disease research and deep learning techniques. Our adept systems will play an effective role in detecting errors based on images taken by modern hand-held technology.
- Deep learning is a section of Artificial Intelligence (AI) that has changed our world like electricity.
- Deep learning allows researchers to create smarter and more interesting AI applications that can perform tasks autonomously without human intervention.
- CNN's popularity has onward dramatically and CNN is now used everywhere. It has obtained remarkable results in the field of image recognition.
- Models created with CNN can be effortlessly used on any platform. Since CNN has been used in well-known studies, we believe we should use CNN to detect disease in livestock.

1.4 Expected Outcome

We will create such a system in which the farmer will take a picture of his infected cattle, along with the description of the diseases of the cattle. In the future, we will build an android application and web based program on this project. We hope this model will make an important contribution to preventing terrible diseases in livestock. Since the trained models will be configured as a cloud-based smartphone app. With the help of this app, a person can diagnose his cattle skin disease for free. Diagnosis and treatment within the stipulated time will greatly reduce the mortality rate of cattle. Due to the veterinary crisis in Bangladesh, this application will also protect ordinary people from fabrication doctors.

1.5 Report Layout

In this report, we have proposed CNN models for animal disease recognition, it consists of six parts shown below:

Chapter 1: Introduction

This section explains an introduction to the research work with its motivation, objectives, and expected outcome in this chapter.

Chapter 2: Background Study

In this chapter, we discuss the literature review, research summary, the scope of the problem, and challenges.

Chapter 3: Research Methodology

In this chapter, we discussed the workflow, data collection process, and implementation requirements of this research.

Chapter 4: Experimental Results and Discussion

The results and experimental evaluation, that is, the results of the research, are graphically processed in this chapter.

Chapter 5: Conclusion and Future Work

This chapter summarizes our research and future work.

CHAPTER 2

Background Study

2.1 Introduction

In this chapter, It will discuss the literature review, the research summary, scopes of the problem, and the challenges we face in carrying out this work. It summarized some of the research work in our work and explained the basic methods, classifiers, and accuracy of their work in the literature review section. In the research summary section, we provide a table in which we show a summary of related work for a better understanding. How we use our CNN model to solve this problem, we explained in the context of the problem section. In the challenge section, we discussed the obstacles we encountered in the research process.

2.2 Literature Review

Many studies have been done on the problems related to the recognition of various animal diseases using traditional machine learning with monitoring systems. As far as we know, no studies are working with deep learning to recognize animal diseases. However, from a review of the previous literature, most papers focus on IoT-based work to monitor several important methods in livestock production. Some of them refer to the Arduino environment, fuzzy logic and some sensors used to monitor diseases and other parameters but do not explicitly define the results. Therefore, the main goal of this study is to classify FMD through the architecture of the accumulative neural network.

Omolbanin Yazdanbakhsh et al. [12] recommended the use of animal-mounted devices with trained monitoring techniques to automatically and continuously check the health of each cow using a presumptive sensor. As a consequence, it was determined that employing the ensemble classifier's wavelet domain yielded just 80.8% sensitivity and 80% specificity. However, the system is dependent on expensive sensor devices and a connected system that is constantly monitored by a computer.

Shivank Vyas et al. [13] suggested utilizing the Internet of Things to identify FMD and Mastitis illness in cattle (Internet of Things). To accomplish this task, many types of sensor devices are used to portray various factors in cattle, including temperature, sound, and mobility. For disease detection, machine learning methods (Neural Networks) and a microcontroller will be used. This article made no indication of the categorization model's accuracy, and the system is dependent on costly sensor devices that must be integrated into each animal.

Mr. V Gokul et al. [14] proposed a strategy for using IoT to enable smart husbandry infrastructure that can detect, notify, and manage illnesses during an impending period, anomaly, urgent scenario, calf delivery time, location monitoring, and disease recognition. Each cattle is fitted with a collar. The sink node and wearable device are designed following the device's infrastructure to the cloud server. However, the system makes no mention of the sensor devices' accuracy. It will carry plenty of costs that are almost insurmountable for disadvantaged farmers.

Meenakshi.M et al. [15] introduced an early detection and monitoring method for cattle health. Numerous sensing devices are used to determine numerous health characteristics of cattle, including respiration, body temperature, and humidity. Sensors are connected through the Arduino UNO interface, and the application will display the sketch and graph via the ESP8266 Wi-Fi module. This approach for early detection of cow health may be utilized in place of a manual system for diagnosing many illnesses. As a result, it demonstrates that the suggested model is not accurate. It will be too unaffordable for impoverished farmers to get all essential sensors.

Ankit R. Bhavsar et al. [16] proposed a structured data storage module for evaluating, storing, and testing data collected through Wireless Sensor Networks for cattle welfare monitoring (WSN). This technology will benefit users such as cattle ranchers, rural health care providers, and veterinarians. The proposed system provides users with instructions and symptoms for possible cattle illness and sickness. As a result, this system requires a constant internet connection and a variety of pricey sensors and storage equipment that are unaffordable to livestock producers.

Vijayashree B.R. et al. [17] established a correlation between cow sickness and the evolution of the health monitoring system via the use of multiple sensors. By using a cattle wellness monitoring method, critical parameters affecting cattle health such as respiration, heartbeat, body temperature, humidity, and rumination are continuously monitored using a microcontroller and various IoT devices such as temperature sensor, gas sensor, light sensor, infrared sensor, and accelerometer. However, the study makes no mention of the suggested system's outcome or the cost of the required sensors for cattle producers.

Ateev Agarwal et al. [18] presented a wireless cow health monitoring system that boosted the wireless device and receiver points through the ATmega16 microcontroller and Zigbee communication. Digital sensors such as a humidity sensor, a body temperature sensor, a perspiration sensor, a heartbeat sensor, and a rumination sensor were employed in the system. LabVIEW software is used as a real-time data observer for monitoring the outputs of many sensors on a personal computer. However, the system makes no mention of the suggested method's accuracy, and the device requires energy and an internet connection to function continuously.

G. Suseendran et al. [19] recommended that a smart monitoring system at a cow farm with sensors that anticipated critical calf health at an early stage and employed a fuzzy logic-based module be emulated using the NS2 and Arduino environments. As a result, the system made no mention of its accuracy, and the high cost of the sensors is intolerable for livestock producers, while the devices are inconvenient for the cattle.

However, based on a review of the prior literature, it seems that the majority of effort has been on IoT-based solutions for monitoring several important systems in cattle. Several of them cited the machine learning method used to diagnose illnesses but did not specify the outcome. Thus, the primary goal of this work is to diagnose external diseases in cattle using a smart deep learning architecture.

2.3 Research Summary

Through data mining, machine learning, and deep learning, various work has been carried out in the detection, classification, and detection of cattle diseases. The technique of machine learning and deep learning in various researches has increased. In the literature review, we discussed different types of research. We found that there is no research on the use of deep learning to detect cattle diseases. Some researchers used traditional techniques to detect cattle diseases and used some images. Therefore, their mentioned method is not friendly with new technologies. We've also noticed that some researchers are using CNNs for higher quality accuracy for other cattle diseases.

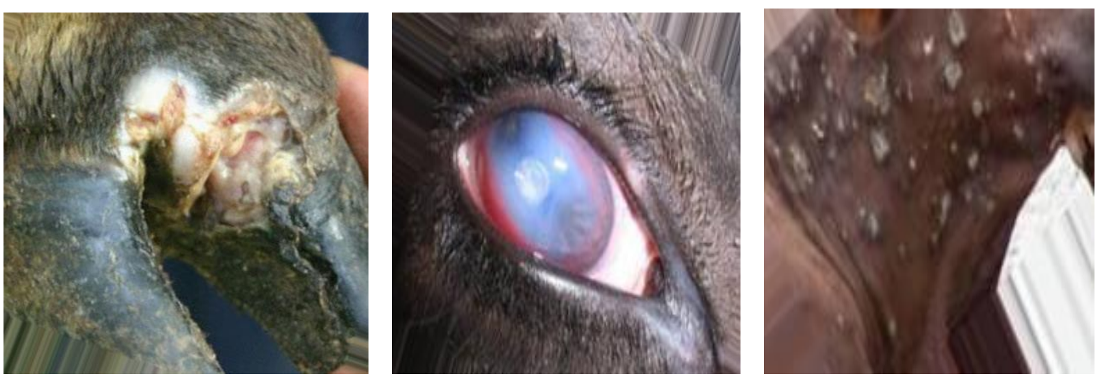
2.4 Scope of the problem

An ordinary problem we found when studying variously related is that the proposed method of detecting cattle diseases cannot improve the overall situation. To get a good detection model, we need to train it on a large data set. They used the surveillance system for the model they proposed. Therefore, their raised system won't work properly with the new test mode. Recently, some notable researchers are using deep learning to solve detection problems and using large data sets to train their models. Their model can work with modern technology, which makes their research relevant and useful to ordinary people. Therefore, we decided to abandon the model of disease detection in favor of deep learning. It will be consistent with the latest technology and the ordinary public will advantage from it.

2.5 Challenges

As we face many problems, collecting pictures of cattle diseases becomes a difficult task for us during our research. We also get tired of recognizing infected cattle. We have collected images by visiting different areas. We have taken pictures of infected cows from many houses, fields, and farms in the village. Not all of these cattle were calm, so there were some troubles. We focus on data sets because a proper data set is an important part of a good model. The symptoms of some cattle diseases are similar. It is very difficult to separate them. It took us several days to generate a good data set.

We also face some problems during the training phase. We used a large data set and the training time was very long. We have also changed the architecture of CNN many times to achieve high accuracy, which is also a challenging task for us. We also generate pre-trained model like VGG -6, Inception-V3. By generating this we have face a lot of challenge. And But in the end, we overcome all the challenges and attain high accuracy. Our CNN model also shows extraordinary performance in new images. External lesions of cattle diseases in Fig. 2.1



1) FMD 2) IBK 3) LSD

Fig 2.1: External Lesions of Cattle Diseases 1) FMD, 2) IBK, 3) LSD

CHAPTER 3
Research Methodology

3.1 Introduction

The main purpose of this research is to establish a model that can properly identify cattle diseases in a shorter period. Helping people connect in animal husbandry is another intention of this work. We have used Convolutional Neural Network in this study and also used three pre-trained models.

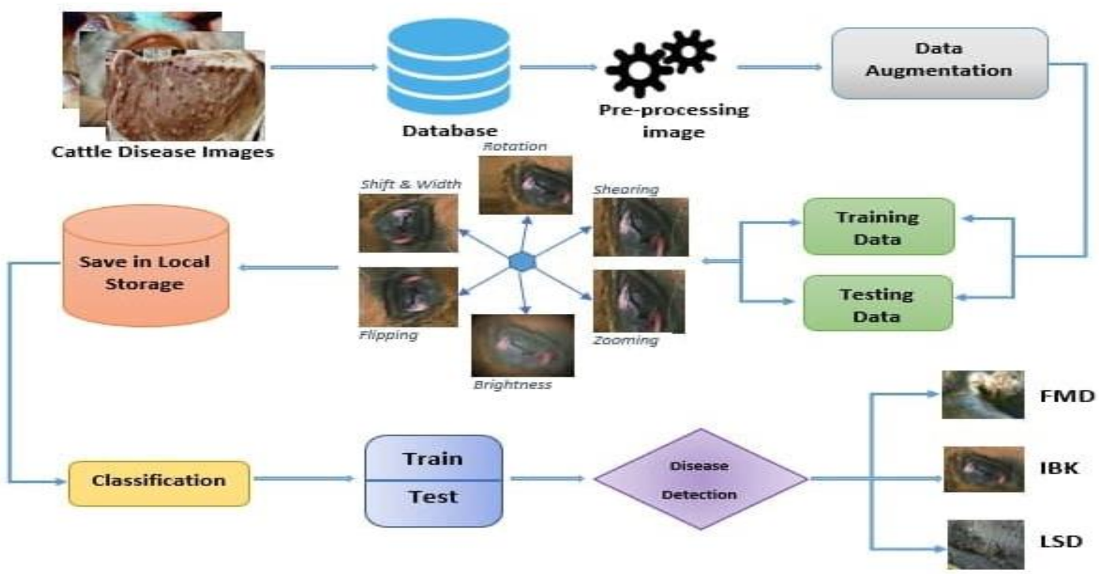


Fig. 3.1: Highlights the working procedure of the proposed architecture

The proposed model explains the steps for this research work. Data sets play an important role in any research work. Before collecting pictures, we got to know about cattle diseases in depth. Then we collected images of infected cattle from different places. In this chapter, we will briefly discuss the description of the disease and the method of data collection. In this chapter, we will also cover all theoretical knowledge.

3.2 Disease Description

An important part of our research is disease research. Makes it easier to understand the effects of various diseases on the skin of cattle. After researching the epidemic, we found three cattle diseases all over Bangladesh. I have identified three complex diseases: Foot and Mouth Disease (FMD), Lumpy Skin Disease (LSD), and Infectious Bovine Keratoconjunctivitis (IBK). The visual symptoms of cattle diseases are shown in Table 3.1.

TABLE 3.1: THE VISUAL SYMPTOMS OF CATTLE DISEASES

Diseases	**Visual Symptoms**
LSD	It causes lumps, swelling, and ulcers on the skin of cattle.
FMD	It depicts cattle with sores on their mouths and tongues, as well as deep lesions on their hooves.
IBK	It demonstrates a tiny low-opacity gap on the membrane, and membrane lesions are typically located centrally on the eye.

Foot and Mouth Disease (FMD) is a highly contagious, epidemic disease that mostly affects cattle worldwide. Aphthovirus are the primary virus responsible for FMD [5]. The pathogen is even capable of traveling 300 kilometers through the air between sick and healthy cattle [4]. For the majority of families in the community, livestock farming is their primary source of income, and their livelihoods are jeopardized as a result of cattle deaths. Early detection is critical for mortality reduction. It is an external cattle disease that impacts livestock production and impedes livestock and animal product import and export trade in particular. Without a firm grasp of the condition in cattle, diagnosis becomes difficult, and a failure to diagnose properly might result in severe difficulties. As a result, rural communities require effective and automated ways of detecting cattle diseases. Domestic animals are susceptible to a range of external infections, including Infectious Bovine Keratoconjunctivitis (IBK), FMD is notable among them, as like Bovine Tuberculosis, Anthrax, Lumpy Skin Disease (LSD), and Bovine Viral Diphtheria (BVD). Fever, blisters on the lips, mouth, and tongue, and pus-filled lesions in the middle of the hooves are typical symptoms of FMD. Following disease recovery, the majority of afflicted animals become weak and vulnerable. Although the disease is not particularly lethal in mature animals, when the generatrix is afflicted, the mortality rate in very young animals is extremely high due to the requirement for milk [5].

Lumpy Skin Disease (LSD) is a worldwide pestiferous, eruptive, and occasionally deadly disease affecting primarily cattle. *Capripox* is the primary pathogenic virus that was most frequently used in conjunction with LSD. Livestock rearing is a significant source of income for the majority of families in the hamlet, and their livelihoods are jeopardized as a result of cattle deaths. Early detection is critical for reducing livestock mortality. It is an external animal disease that impacts livestock production and impedes livestock and animal product import and export trade in particular. Without a firm grasp of the condition in animals, diagnosis becomes challenging, and a failure to diagnose properly can result in a complex situation. As a result, rural communities require effective and automated ways of detecting cattle diseases such as LSD [20].

Infectious Bovine Keratoconjunctivitis (IBK), or Conjunctivitis, is a common, highly contagious eye disease that primarily affects the calf. This is caused by *Moraxella Bovis* and the infection can lead to loss of vision in acute cases. The duration is usually 23 days, with small, faintly opaque spaces on the membrane visible every 2 days, with membrane lesions usually in the center of the eye [7].

3.3 Data Collection

The most difficult aspect of this study was gathering data. Various locations, such as veterinary hospitals, cattle farms, the internet, and so on, were in charge of the data. Veterinarians checked the information.

3.4 Dataset Description

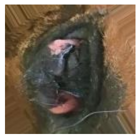
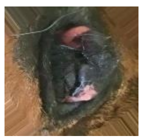
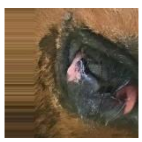
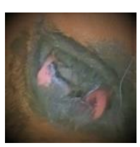
The total number of raw photos is 600, divided into three classes: FMD, LSD, and IBK, with 250, 200, and 150 images dispersed for each class. The images have been reduced to 32x32 pixels for CNN, 224x224 pixels for VGG-16, and 299x299 pixels for Inception-V3. They are all in RGB format with a scale of 0-255. There are 480 photos in the training dataset and 120 images in the testing dataset [21]. Table 3.2 shows the categories of the data sets that were collected.

TABLE 3.2: TOTAL IMAGES OF CATTLE DISEASES IN DATASET

Diseases	Number of raw images	Number of raw and augmented images	Number of Training images	Number of Testing images
FMD	250	2500	2000	500
LSD	200	2000	1600	400
IBK	150	1500	1200	300
Total	**600**	**6000**	**4800**	**1200**

In deep learning neural networks, data augmentation is required, especially when the dataset contains fewer data points. As a result, it aids in the expansion of the dataset, the removal of over-fitting, and the regularization of the dataset. Shifting, resizing, rotating, flipping, shearing, zooming, and altering brightness and contrast improvement are some of the data augmentation techniques [22]. For supplementing data, this model employed the Keras library, which contains a class named ImageDataGenerator. The Keras library is used in a variety of Data Augmentation approaches, as shown in Table 3.3.

TABLE 3.3: DIFFERENT TYPES OF DATA AUGMENTATION TECHNIQUES

Augmentation Images	**Augmentation techniques**
 (Original image)	Load original image.
 (Rotation 90˚)	datagen = ImageDataGenerator(rotation_range=90)
 (Flipped)	datagen = ImageDataGenerator(rotation_range=180, horizontal_flip=True)
 (Shift width and height)	datagen = ImageDataGenerator(width_shift_range=0.3, height_shift_range=0.2)
 (Shearing and zooming)	datagen = ImageDataGenerator(shear_range=0.5, zoom_range=0.6)
 (Brightness enhancement)	datagen = ImageDataGenerator(brightness_range= [0.1,0.3])

3.5 Statistical Analysis

We collected a total of 600 images of affected animals from different locations. We collected 250 infected FMD images and 200 LSD images and 150 IBK disease images. In the picture below we have highlighted the ratio of three diseases through a piechart in Fig. 3.2.

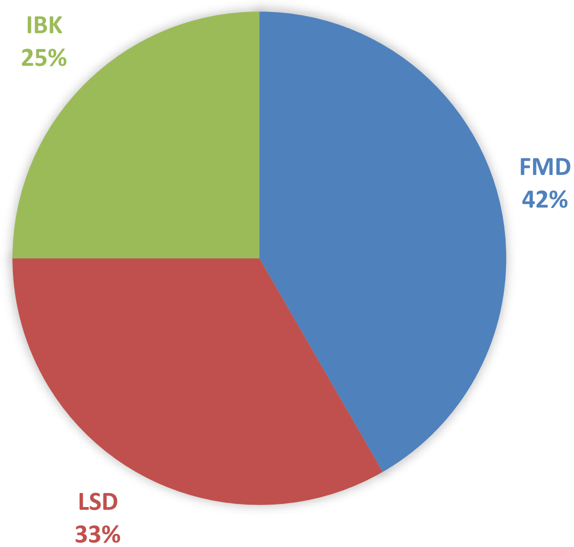


Fig 3.2: Ratio of FMD, LSD, and IBK disease images

3.6 CNN Model for Disease Recognition

CNN is a sort of feed-forwarding neural network that uses a deep configuration to perform convolutional or parallel calculations [23]. It's a powerful network that extracts features from images using filters. In comparison to typical feed-forwarding neural networks, CNN's architecture was inspired by the sort of neurons found in the human brain, which enable it to recover vital information from images [24]. The parameters of the layers include some of the trainable filters (or kernels) that keep a limited capacity territory but improve it throughout the depth of the input density [9]. Figure 3.3 depicts the CNN architecture.

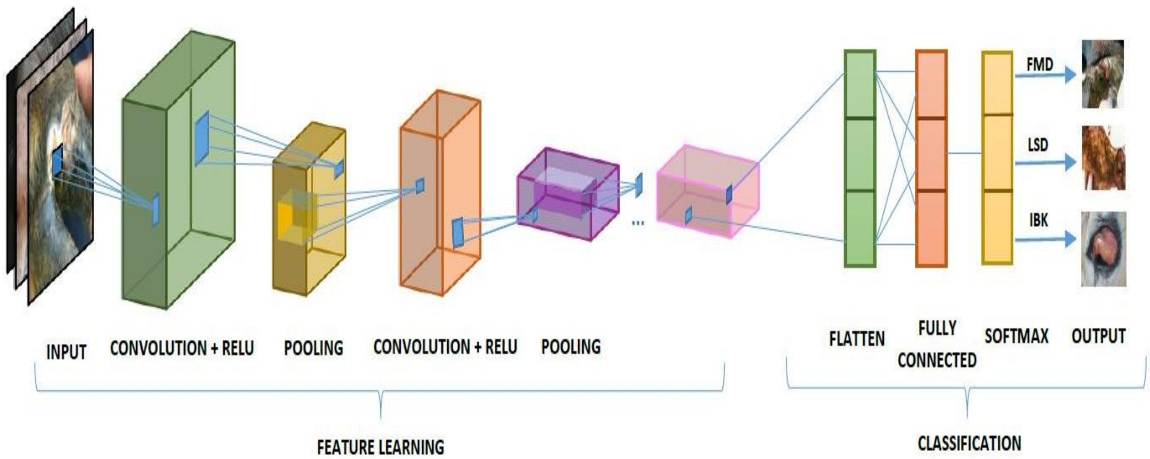


Fig 3.3: The architecture of the Convolutional Neural Network

CNN is useful in a variety of fields, including image segmentation, classification, and recognition. Because CNN has reached current image recognition, it was chosen to identify the cattle disease picture collection in this proposed architecture. Feature Extraction and Classification are the two main aspects of CNN. Pooling and convolution layers are used in feature extraction, while a fully connected layer is used in classification [25].

3.6.1 Convolutional layers

Convolutional Layer is the initial layer of a traditional CNN and is responsible for extracting the features of the input images. This layer is responsible for calculating the output to the neurons associated with local territories. Multiplying regions and weights yield the value of each filter. Each image in these files has a width and height of 32x32 pixels and a depth of 3 (since it is an RGB channel) [24]. A single or several convolutional layers would generate the feature vector, correspondingly. Each layer is composed of a large number of kernels or filters. Convolutional filters are applied to the input images. Thus, the depth of the resulting feature map *Ki, j (n1)* is proportional to the total number of convolution kernels [9]. The eq.1 is delivered in this model for convolution operation are,

$$\mathrm{X}^{(n)} = \sum_{j=1}^{a_i^{(n-1)}} K_{i,j}^{(n-1)} * X_j^{(n)} + b_i^{(n)} \quad (1)$$

Here, the $N\ th$ convolution layer using bias b, as the output of $Xi\ (n)$, K is considered as kernels. The convolution function of a 5 × 5 input map with a 3 × 3 filter that produces a 3 × 3 feature map is shown in Figure 1 below. 3.4.

1	**1**	**1**	**0**	**0**
0	**1**	**1**	**1**	**0**
0	**0**	**1x1**	**1x0**	**1x1**
0	**0**	**1x0**	**1x1**	**0x0**
0	**1**	**1x1**	**0x0**	**0x1**

Image

4	**3**	**4**
2	**4**	**3**
2	**3**	**4**

Convolved Feature

Fig. 3.4: Convolution function of 5 × 5 input map with a 3 × 3 filter

3.6.2 Pooling layers

Following the convolutional layer, a pooling layer is used to collect features from maps formed by convolving a filter over an image. Typically, its purpose is to reduce the number of parameters, or in other words, to lower the network's computing cost. The study employed 2x2 (two by two) pixels with a stride size of two pixels, which means that the pooling layer will gradually reduce the dimension of each feature map by a factor of 2 [25].

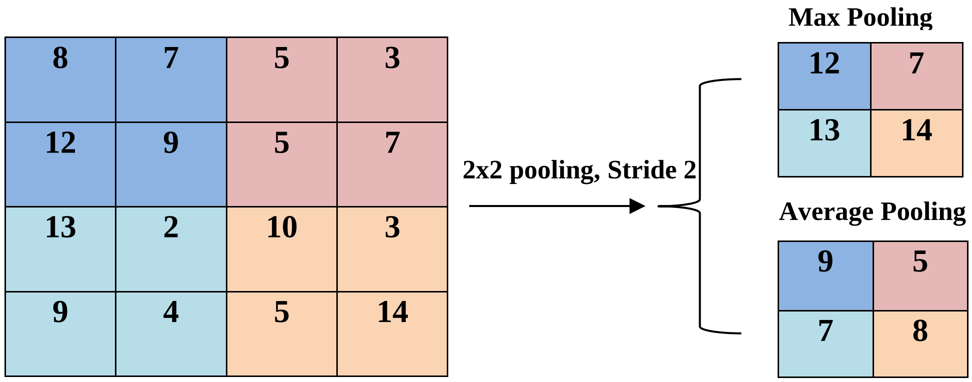


Fig. 3.5: Max pooling and Average pooling operation 2 x 2 filters and stride 2.

3.6.3 ReLU

For hidden layers of NN (Neural Network), the Rectified Linear Unit (ReLU) is the most often employed activation function. It overcomes the Sigmoid function's restrictions, which were that it could only be used for binary classification. ReLU is a program that solves this problem and is mostly used in image recognition for multi-class categorization. It carries out a non-linear operation and decreases vanishing gradients [26]. ReLUs in eq.3 would be applied to the nonlinear operation of these outputs to $Xi\ (n)$ in eq.2 by performing the convolution layer on the cattle picture dataset.

$$R_i^{(n)} = R(X_i^{(n)}) \quad (2)$$

$$R_i^{(n)} = max(0, R_i^{(n)}) \quad (3)$$

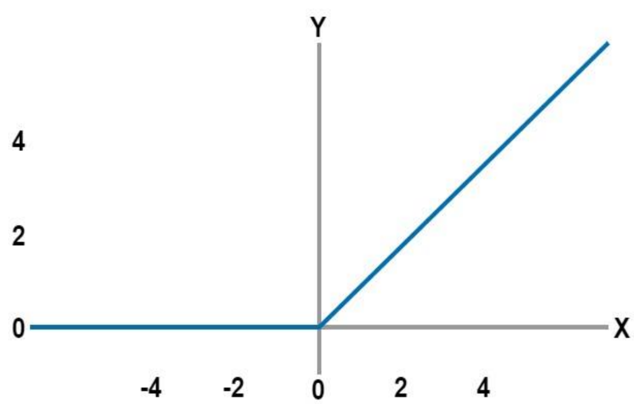


Fig. 3.6: ReLU Operation

3.6.4 Softmax

The Softmax function can recognize objects between 0 and 1 using probability theory [27]. It is mainly used for multi-class identification. This is applied to the output level by eq.4.

$$x_i^{(n)} = f\,(v_i^{(n)}),$$

$$\text{Where,} \quad v_i^{(n)} = \sum_{i=1}^{u_i^{(n-1)}} z_{i,j}^{(n-1)}\, x_i^{(n-1)} \qquad (4)$$

Here, $z_{i,j}^{(n)}$ is the weight performed by the fully connected layer to classify the diseases of the three mainstream exterior cattle, and f is referred to as a transfer function that shows nonlinearity [9].

3.6.5 Fully Connected layers

The term "Fully Connected Layer" refers to a layer in which all of the levels' inputs are connected to each activation unit. The last layers are quite coherent, as they take data from the previous levels and generate an accurate output. Numerous CNN variants, including VGG, AlexNet, and GoogleNet, make use of Fully Connected Layers within the ILSVRC. Fully Connected Layers are also required for non-linear combinations to combine the output with the flat portion of the output. When CNN and Fully Connected Layers are combined, the outcome is the same [28].

3.6.6 Dropout

Dropout is a basic method of preventing overfitting in the neural network. Dropout in a neural network refers to the removal of both hidden and visible nodes. In our study, dropout was applied in the fully linked layer to prevent overfitting. It provides an efficient regularization strategy to decrease overfitting and enhances model complexity in CNN. A SoftMax activation function is used in the last fully connected layer, which is a much more comprehensive stochastic activation function with multi-class classification in CNNs. This function assigns a probability value between 0 and 1 to the item.

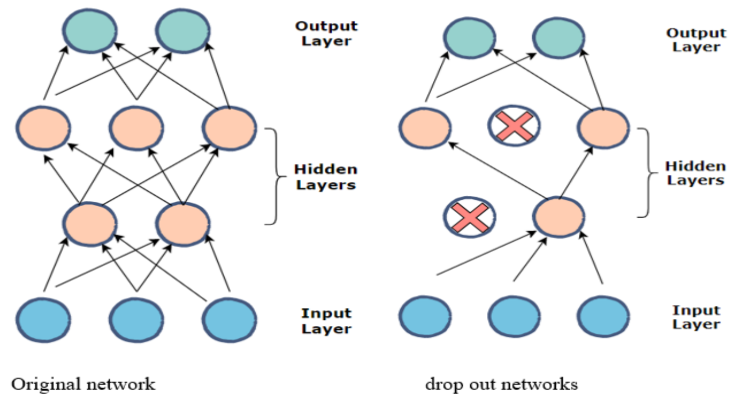


Fig. 3.7: Original and dropped out neural network.

3.6.7 Learning Algorithm

The first level of convolution extracts low-level features such as curves, edges, corners, and lines. Global features are learned in the next convolutional layer. CNN uses backpropagation (a training process) to learn features. The four different parts of the backpropagation learning algorithm are forward propagation, loss function, backpropagation, and weight update. By the onward pass, CNN records training images and routes the images to the entire network. First, all weights or filter values are initialized randomly. In the first layer of convolution, CNN cannot check low-level features. So when it comes to classification, CNN cannot make the right decision. Some commonly used loss functions are classification cross-entropy, binary cross-entropy, sparse classification cross-entropy, and mean square error. To give CNN a true label forecast, the damage has been minimized. To find out which inputs do the most damage to the network, a reverse pass must be performed through the network. Use CNN throughout the training set and use the stochastic gradient descent to overcome the high cost of backpropagation. The process of moving forward, backward, running the loss function, and updating the weight is repeated until the loss function reaches the threshold. The network is well trained because the weights of the layers are adjusted correctly.

3.7 VGG-16

VGG-16 is a convolutional neural network architecture developed by the Visual Geometry group. It was used to win the 2004 ILSVR or ImageNet competition. It is deemed to be the best visual model masonry to date. It has a 16-layer CNN of its own. In VGG-16, smaller convolutional layers combine to build a bigger layer, increasing the layer's efficiency [10]. The VGG-16 architecture is depicted in Figure 3.8. The Convolutional layer is designated by the symbol Conv, and the image should have a resolution of 224*224 pixels.

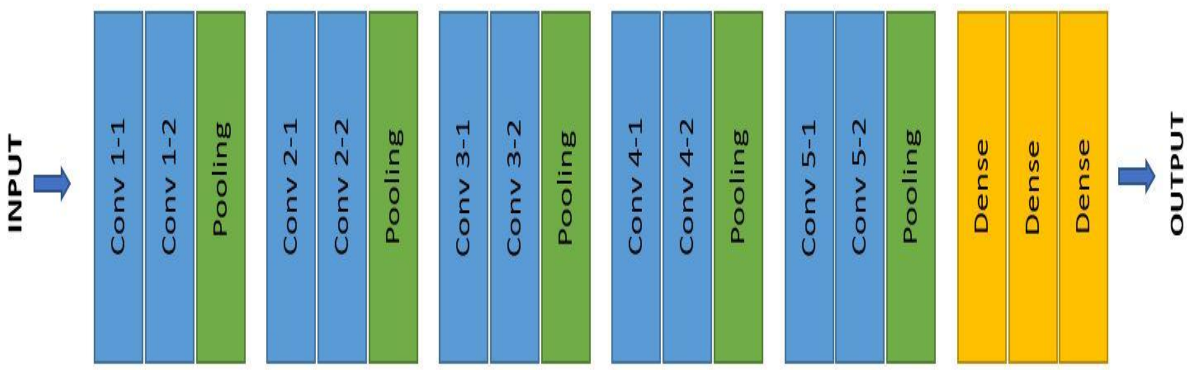


Fig. 3.8: Architecture map of VGG-16.

3.8 Inception V3

Inception-V3 is a widely used image recognition model that has been found to improve accuracy on the ImageNet dataset. By changing earlier induction design, mainly focuses on computational power. It is made up of 42 layers. In comparison to VGG, inception's computed efficiency is substantially higher in terms of processing resources and parameters. By announcing factorized convolutions, as well as broad filter size, imbalanced convolutions, and factorization into smaller convolutions, the genuine Inception Network model has been refined [11]. Because it contains 24 million parameters and the image size must be 299*299 pixels, the Inception-V3 architecture performs better than classic CNN and VGG-16 architecture [29].

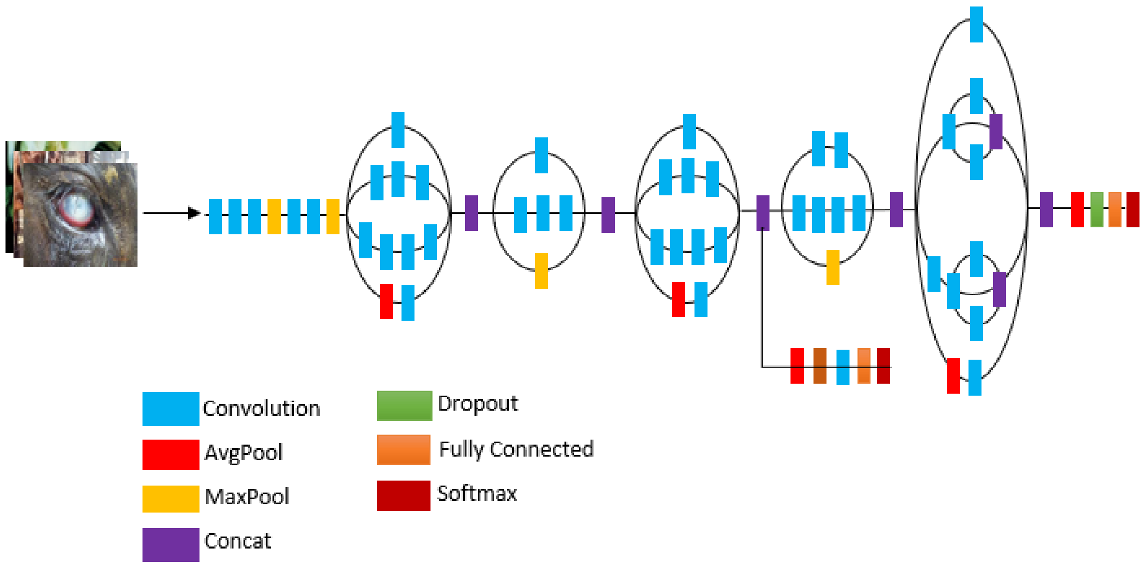


Fig 3.9: The schematic representation of Inception-V3.

This Inception V3 architecture has been modified by us. This model has been added as a base model in one layer. We've added three new layers after this one. The final layer of this modified architecture is a dense layer with the following output shape: (None, 3). With 100 epochs, we achieved 98% training accuracy and 96% testing accuracy using this modified pre-trained model.

3.9 Implementation Requirements

We used smartphone cameras to take pictures of animal diseases. To protect it, we used Jupiter notebooks to change and reduce image quality. Due to memory limitations, we reduced the quality of the image. We conserve our datasets in Google Drive. We use Google Collab. We used Python 4.4 in our study.

3.10 Performance Metrics

Seven assessment indicators are used to track the success of the categorization model. The evaluation of the metrics is as follows [30]:

TP (True Positive): These are the cases where we have predicted yes and so it has happened later.

FP (False Positive): In such cases yes has been predicted, but something negative has happened.

TN (True Negative): These are the cases where we have not predicted and then something negative has happened.

FN (False Negative): Such cases have not been predicted, but something positive has happened.

Accuracy, Precision, Sensitivity, Specificity, Error Rate, F_1-score, and G-mean for finding recognition performance of each class of dataset,

- Accuracy $= \frac{TP+TN}{\mathrm{TP+TN+FP+FN}}$
- Precision = $\frac{TP}{\mathrm{TP+FP}}$
- Sensitivity = $\frac{TP}{\mathrm{TP+FN}}$
- Specificity = $\frac{TN}{\mathrm{TP+FP}}$
- Error Rate $= (1 - Accuracy)$
- F_1-score $= 2 \times \frac{\mathrm{Precession \times Sensitivity}}{\mathrm{Precession + Sensitivity}}$
- G-mean = $\sqrt{Sencitivity \ \times Specificity}$

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

We collect images of external cattle diseases from different locations throughout the year. We use cloud-based storage to store our data sets and models. We also use cloud-based notebooks to train our models. In our research, we used CNN to build a model that can detect animal diseases. We have proposed a CNN model called Convolutional Neural Network (CNN) for cows suffering from external diseases and achieved higher accuracy. In addition to CNN, we also used three pre-trained models. We used Traditional CNN, VGG16, and Inception v3. In this study, Inception v3 performed better than other pre-trained models. In our research process, we focus on our data set to build better models. In this chapter, we will briefly describe our test results.

4.2 Experimental Results & Analysis

The research is based on a data set of 6000 images with three different categories. We use Jupiter Notebook to train our model. We used a 32 × 32 pixel convolution filter in each model in this study. In the following sections from 4.2.1 to 4.2.3, we briefly discuss all models and their related information [2].

Python Keras is the most widely used library for recognizing supplementary tasks. Traditional CNN, VGG-16, and Inception-V3 are three well-known CNN technologies that were used in the model. As a result, the Inception-V3 algorithm received the highest score among the tested algorithms. Inception-V3 for Cattle Diseases Detection achieved training and testing accuracy of 98% and 95%, respectively. Different types of classification results are shown in Table 4.1.

TABLE 4.1. DIFFERENT TYPES OF CLASSIFICATION RESULTS

Evaluation Matrix	**Accuracy**	**Precession**	**Sensitivity**	**Specificity**	**G-mean**	**F_1-score**	**Error rate**
CNN	92%	90%	90%	94%	92%	91%	8%
Inception-V3	95%	93%	93%	96%	94%	92%	5%
VGG-16	91%	87%	89%	94%	90%	86%	9%

Table 4.1 displays the many types of classification results determined by several evaluation matrices, such as Accuracy, Precision, Sensitivity, Specificity, G-mean, F1-score, and Error or misclassification rate of CNN, Inception-V3, and VGG-16 models. In comparison, the Inception-V3 received the best results.

Before the usage of the pre-educated models, we centered deeply on developing a brand CNN version for this study. After two hundred epochs, the proposed conventional CNN accomplished 93% training accuracy and 90% testing out accuracy. The conventional length of the CNN enter photograph is 224 × 224 pixels. In this version, we used the sparse express pass entropy because of the loss feature and the stochastic gradient (SGD) because of the optimizer. Using the sci-kit learn mistakes matrix module, we generated the confusion matrix supplied through Traditional CNN. Fig. 4.1. represent the CNN confusion matrix of the proposed model [2].

Fig. 4.1: Confusion matrix for traditional CNN model.

The plot graph of the traditional CNN is given below in Fig. 4.2.

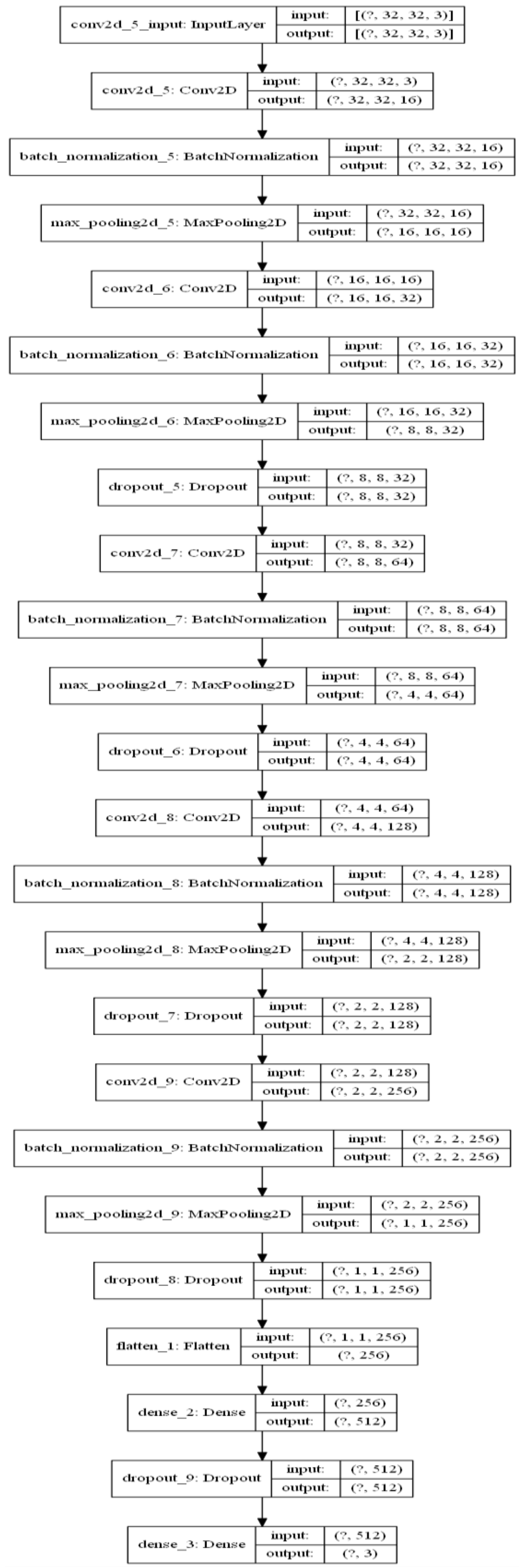


Fig. 4.2: Plot of traditional CNN graph.

Traditional CNN used 527,715 params in total, with no non-trainable params. In Fig 4.3, we show a model summary of our traditional CNN.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_5 (Conv2D)            (None, 32, 32, 16)        448
_________________________________________________________________
batch_normalization_5 (Batch (None, 32, 32, 16)        64
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 16, 16, 16)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 16, 16, 32)        4640
_________________________________________________________________
batch_normalization_6 (Batch (None, 16, 16, 32)        128
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 8, 8, 32)          0
_________________________________________________________________
dropout_5 (Dropout)          (None, 8, 8, 32)          0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 8, 8, 64)          18496
_________________________________________________________________
batch_normalization_7 (Batch (None, 8, 8, 64)          256
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 4, 4, 64)          0
_________________________________________________________________
dropout_6 (Dropout)          (None, 4, 4, 64)          0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 4, 4, 128)         73856
_________________________________________________________________
batch_normalization_8 (Batch (None, 4, 4, 128)         512
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 2, 2, 128)         0
_________________________________________________________________
dropout_7 (Dropout)          (None, 2, 2, 128)         0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 2, 2, 256)         295168
_________________________________________________________________
batch_normalization_9 (Batch (None, 2, 2, 256)         1024
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 1, 1, 256)         0
_________________________________________________________________
dropout_8 (Dropout)          (None, 1, 1, 256)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 512)               131584
_________________________________________________________________
dropout_9 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_3 (Dense)              (None, 3)                 1539
=================================================================
Total params: 527,715
Trainable params: 526,723
Non-trainable params: 992
_________________________________________________________________
```

Fig 4.3: Model summary of proposed traditional CNN.

In Figures 4.4 and 4.5, the accuracy and loss of typical CNN training and testing are presented. The training accuracy increases steadily as the iteration time increases, as seen in Figure 4.6.

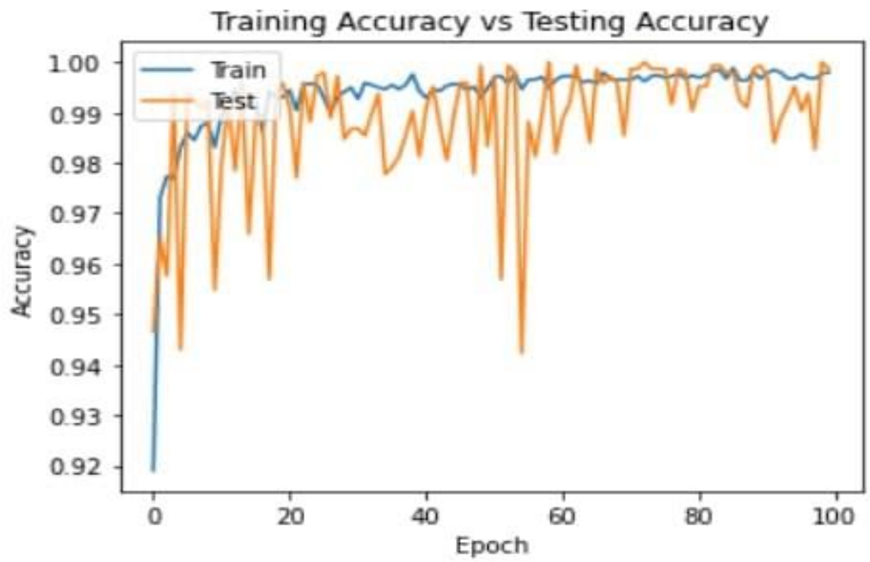


Fig. 4.4: Training accuracy vs testing accuracy of traditional CNN.

The testing loss decreases as iteration time decreases, as shown in Fig. 4.6. After 100 iterations of testing, the model suffered an unanticipated loss after 52 iterations, but the loss decreased again as the number of iterations increased.

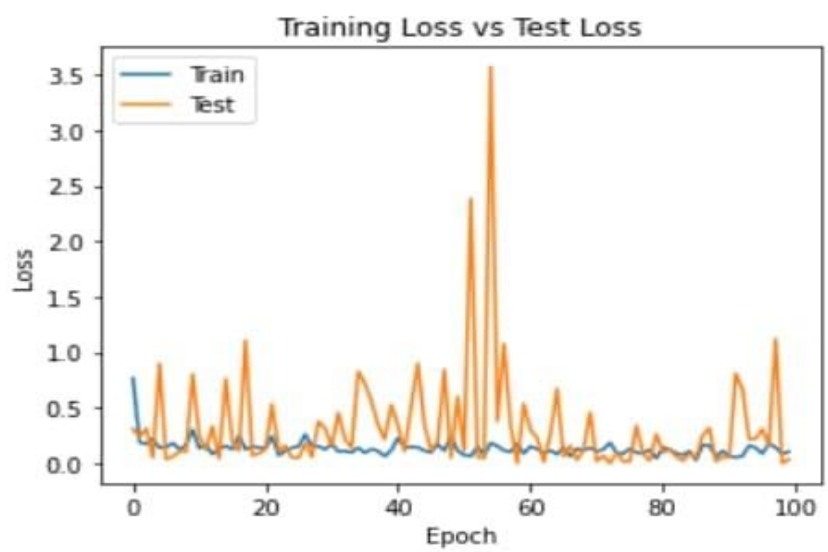


Fig. 4.5: Training loss vs testing loss of traditional CNN.

We achieved 88% training accuracy and 83% testing accuracy after 100 epochs of VGG16. Figure 4.6. Represent the proposed model's VGG-16 confusion matrix.

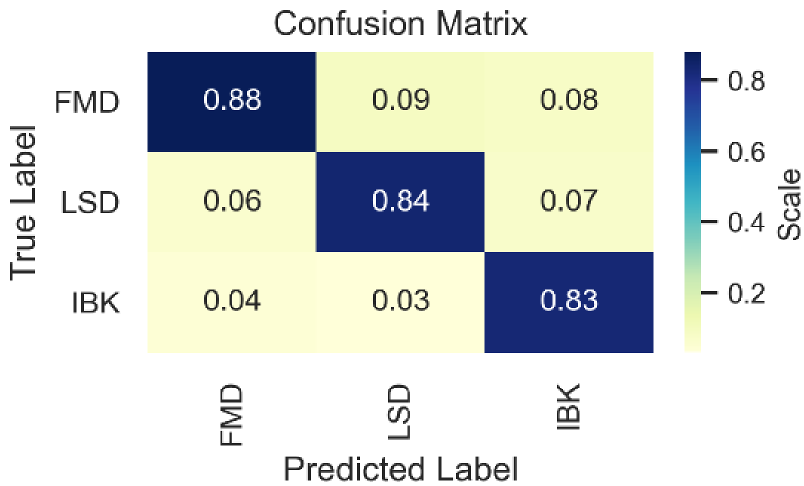


Fig. 4.6: Confusion matrix for VGG-16 model.

VGG-16 used 134,264,641 params in total, with no non-trainable params. In Fig 4.7, we show a model summary of our VGG-16.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 224, 224, 64)      1792
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 224, 224, 64)      36928
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 112, 112, 64)      0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 112, 112, 128)     73856
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 112, 112, 128)     147584
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 56, 56, 128)       0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 56, 56, 256)       295168
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 56, 56, 256)       590080
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 56, 56, 256)       590080
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 28, 28, 256)       0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 28, 28, 512)       1180160
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 28, 28, 512)       2359808
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 28, 28, 512)       2359808
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 14, 14, 512)       0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 14, 14, 512)       2359808
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 7, 7, 512)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dense_1 (Dense)              (None, 4096)              102764544
_________________________________________________________________
dense_2 (Dense)              (None, 4096)              16781312
_________________________________________________________________
dense_3 (Dense)              (None, 3 )                4097
=================================================================
Total params: 134,264,641
Trainable params: 134,264,641
Non-trainable params: 0
_________________________________________________________________
```

Fig 4.7: Model summary of VGG-16.

Model summary of modified Inception V3 is shown below in Fig. 4.8.

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
inception_v3 (Model)         (None, 8, 8, 2048)        21802784
_________________________________________________________________
global_average_pooling2d_2 ( (None, 2048)              0
_________________________________________________________________
dropout_2 (Dropout)          (None, 2048)              0
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 8196
=================================================================
Total params: 21,810,980
Trainable params: 8,196
Non-trainable params: 21,802,784
_________________________________________________________________
```

Fig 4.8: Model summary of Inception V3.

Table 4.9 shows the confusion matrix of a modified Inception V3 model.

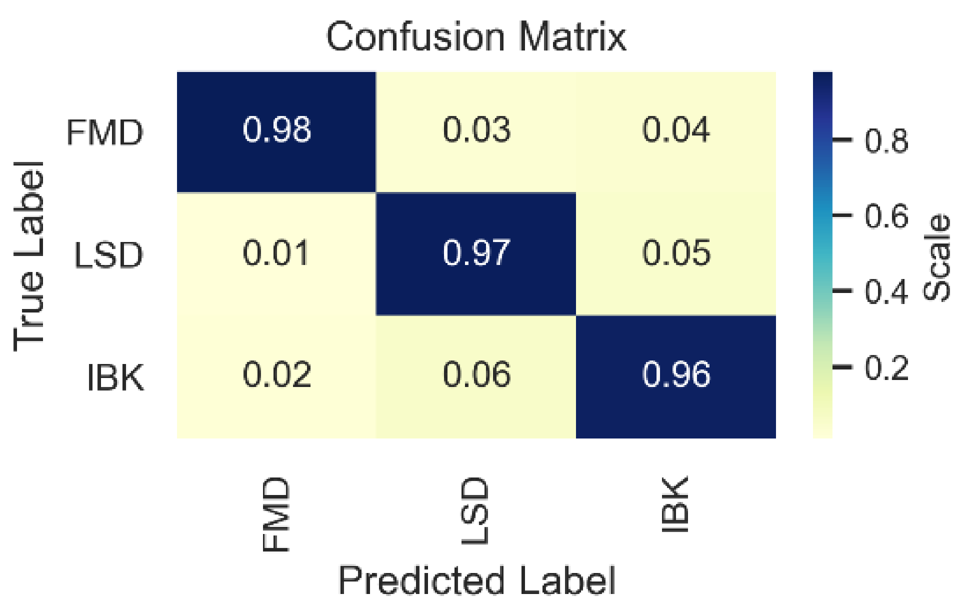


Fig. 4.9: Confusion matrix for Inception V3 model.

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4.3 Summary

To improve the accuracy of a model, each model must have a clear understanding of all meanings and individual performance. These parameters are used to find the best value for the individual part. This report used 80% training data and 20% testing data to achieve the expected results. This model used three well-known CNN architectures like CNN, VGG16, and Inception V3. The accuracy of training and testing of external bovine disease classification in Inception V3 reached 98% and 96%, respectively.

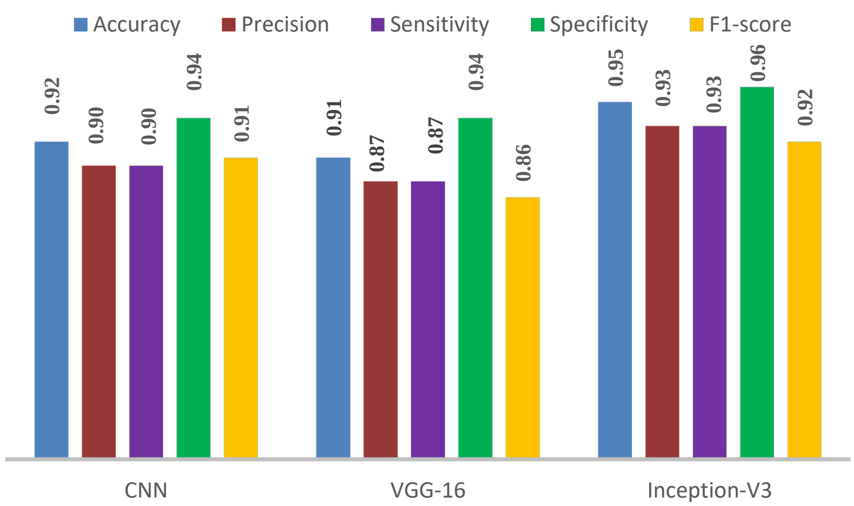

Fig. 4.10: Bar chart of the performance of CNN, VGG-16, and Inception-V3.

The performance of CNN, VGG-16, and Inception-V3 are compared in Fig. 4.10. It represents that the Inception-V3 has acquired 96% Specificity, 95% Accuracy, 93% Precision, 93% Sensitivity, 92% F1-Score comparison between CNN and VGG-16.

CHAPTER 5

Conclusion and Future Work

5.1 Conclusion

External diseases of cattle are recognized and diagnosed in this work utilizing deep learning algorithms, including CNN, VGG-16, and Inception-V3. Inception-V3 produced the best-expected result of all the algorithms tested. It has a sensitivity of 93% and a specificity of 96%. By analyzing the datasets, the disease's classification was enhanced and it was granted acknowledgment. Transfer learning approaches to aid in improving the suggested model's accuracy. The constraints of this work include a small amount of raw data, which reduces accuracy and increases loss at a rapid rate of repeats. Inadequate information and a paucity of exact diagnostic tools can result in inaccurate outcomes. Additionally, we are interested in working with important internal and external disorders in the future. This research will assist farmers at all levels in swiftly detecting and treating external pandemic diseases of cattle [2].

5.2 Implication for Future Study

The use of systems based on artificial intelligence makes our day-to-day easier than ever. Artificial intelligence transforms the lot like electricity. We would like to make our CNN models available in an Android app. Smartphone and Internet users are increasing day by day. An easy-to-use mobile application with attractive GUIs will come in handy for pastoralists and general people. Now, our CNN model can detect images of three diseases. In the future, we will increase the number of diseases so that many diseases are easily recognized by one app. Future research will generate more powerful data sets. In the future, we will also concentrate on the accuracy of our traditional CNN model. We would like to publish the model as a pre-training model for various external animal diseases. With the help of a veterinarian, the model can be enlarged and brought forward.

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APPENDIX

The published paper of our research is attached as an appendix to this affiliation, which was published in the named **"THE 12th INTERNATIONAL CONFERENCE ON COMPUTING, COMMUNICATION AND NETWORKING TECHNOLOGIES (ICCCNT)"** conference. July 6-8, IIT-Kharagpur, India.

Cattle External Disease Classification Using Deep Learning Techniques

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***Abstract*— Cattle external diseases like Foot and Mouth Disease (FMD), Lumpy Skin Disease (LSD), and Infectious Bovine Keratoconjunctivitis (IBK) are the most highly contagious diseases around the world. Early diagnosis is crucial for controlling these diseases. Traditional Convolutional Neural Networks is the most used architecture in the state-of-the-art of image processing and computer vision field. According to our knowledge, no other system for cattle disease detection in the husbandry farm has been introduced by using deep learning techniques. This proposed model referred to early detect the most common external diseases using several CNN architectures like conventional deep CNN, Inception-V3, and VGG-16 in the field of deep learning. All necessary steps for performing the diseases detection model are completely described in the paper, from the data collection to the process and outcome. The proposed system is established to be effective, acquiring results with 95% accuracy, which may reduce human errors in the identification process and will be helpful to recognize diseases for veterinarians and husbandry farmers.**

Keywords*— *Cattle disease, LSD, FMD, IBK, CNN, VGG-16, Inception-V3, Data Augmentation, Veterinarians, Husbandry.

I. Introduction

Cattle disease is a great impedance to domestic animals around the world leading to high fatality to them. To decrease fatality rates, it is formed that it's very effective to early recognize diseases. The conventional techniques are time-wasting and error-prone as they call for veterinarians to use their experiences and naked eyes in the recognition process. Sometimes the disease diagnosis is erroneous and prescribed the incorrect solution. That's causing the deaths of the cattle and great impact to reduce the economic growth of the livestock industry of a country. Therefore, high efficient and automated techniques detecting the cattle lesions cells are required [1].

There are several cattle diseases, e.g. Anthrax, Bovine Viral Diarrhoea (BVD), TB (Bovine Tuberculosis), Foot and Mouth Disease (FMD), Lumpy Skin Disease (LSD), Infectious Bovine Keratoconjunctivitis (IBK), and so forth. This paper focuses on the early detection of the three most mainstream and perilous external lesions diseases such as FMD, LSD, and IBK.

According to a newspaper on 16 October 2018, found that about 55.13 million domestic animals in Bangladesh are affected by FMD [2]. Another news found that over 100 cows died on FMD and more than 1,500 have been affected in Joypurhat's Kalai Upazila on July 10, 2017 [3]. It is an epitheliotropic, transboundary, and highly contagious viral disease infecting cattle, buffalo, sheep, goats, and wild animals around the earth [4] and caused by *Aphthovirus*. It expositions the lesions on the mouth, tongue, and foot. It ejects saliva from the mouth and coming out pus and blood from the foot.

On 11 January 2020, found that 2,62,535 cattle, with 9,993 calves have been affected by LSD out of 52,81,068 cattle in Chittagong, causing 26 cattle with 11 calves to die and 43 infected cattle are victims of abortion. It is a contagious, transboundary viral disease of buffalo and cattle caused by LSDV (Lumpy Skin Disease Virus). As a result, the wound skin of infected cattle shows a nodular shape with a radius of 5-25 mm [5].

Infectious Bovine Keratoconjunctivitis (IBK) or pinkeye is a common, extremely contagious ocular disease moving primarily calves. It is caused by *Moraxella bovis*, the infection could result in vision loss in acute cases. The period is usually 2-3 days, with a tiny low opaque space showing on the membrane at intervals of 2 days and membrane lesions are normally central in location on the eye [6].

At present, Computer Vision has been playing an important role in rearing cattle and protecting livestock. There are some early detection techniques for diagnosis the external cattle diseases and the most common are ANN (Artificial Neural Networks) and CNN [7]. This research is proposed to detect external cattle disease using CNN (Convolutional Neural Network) techniques, and it's two common architectures like VGG-16 and Inception-V3.

CNN is known as feed-forwarding ANN that has some features as pool operation, generalization, regularization, and territorial connection, which form it feasible to practically diminish network complicity [8]. VGG-16 is a CNN architecture that has sixteen convolution layers and it is a pre-trained model of Keras library [9]. Inception-V3 is a CNN architecture for assisting in data exploration, object recognition and it was started as a GoogleNet module [10].

The sequence of this procedure is presented below:

a) The introduced CNN algorithms classify three types of external diseases of cattle that detect FMD, LSD, and IBK images with the least error.

b) Identification of external and most common cattle diseases through automated systems will help to reduce the strenuous observing work on a large farm for husbandry farmers.

This paper is arranged as follows. The discussion of the related work is in section II. In section, III discusses Dataset, Data Augmentation, Methods, Convolutional Neural Network architecture, VGG-16, and Inception-V3. The IV section is described in the Identification Performance Assessment. In the final section, V is the conclusion of this paper.

II. RELATED WORK

Omolbanin Yazdanbakhsh et al. [11] proposed the usage of animals mounted devices with knowledgeable surveillance methods to automatically and constantly monitor the wellness of every cattle form of a presumptive sensor. As a result, it showed that using the wavelet domain of the ensemble classifier achieved only 80.8% sensitivity and 80% specificity. However, the system depends on high costly sensor devices and a wired system with always a computer monitoring process.

Shivank Vyas et al.[12] proposed to detecting FMD and Mastitis disease in cattle using IoT(Internet of Things). Executing this job, different kinds of sensor devices are utilized to depict different parameters in cattle such as temperature, sound, and motion. Machine learning algorithms (Neural Networks) and micro-controller will be utilized for the recognition of the diseases. This paper didn't mention any accuracy of this classification model and the system depends on expensive sensor devices and it must be included in every cattle.

Mr. V Gokul et al.[13] introduced a method is to make the husbandry infrastructure will be smart and identify, inform, and handle diseases at the imminent period, abnormality, critical situations, calf delivery time, location tracking, and recognize diseases with the help of IoT. Every cattle is attached to a wearing device. The sink node and wearing device are planned depends on the infrastructure of a device to cloud server. However, the system doesn't mention the accuracy of the sensor devices. It will be holding a lot of expenses that almost unbearable for impoverished farmers.

Meenakshi .M et al.[14] proposed an early detection of cattle health observing system. Different kinds of sensing devices are applied for identifying several health attributes of the cattle, like respiration, body temperature and, humidity, etc. Sensors are used the Arduino UNO interface and it will use the ESP8266 Wi-Fi module to show the sketch and graph on the application. This early detecting cattle wellness monitoring process can be used instead of a manual system for identifying several diseases. Hence, it doesn't show any accuracy of the proposed model. It will be expensive to buy every necessary sensor for impoverished farmers.

Ankit R. Bhavsar et al.[15] considered a formatted data storage module for analyzing, storing, and testing the data utilized in cattle welfare monitoring based on Wireless Sensor Networks (WSN) This system will be helpful to users such as cattle farmers, health operators in rural areas, and also veterinarians. Using the proposed system, users get instructions and syndromes of the probable disease and sickness of the cattle. Hence, this system needs an uninterrupted internet connection and several types of expensive sensors and storage devices that unbearable for husbandry farmers.

However, from the observation of the previous literature, most of the works focused on IoT-based solutions to monitor different critical systems of cattle. Some of them have mentioned the machine learning algorithm used for detecting diseases but not clearly defined the result. So, the main objective of this study is to classify the cattle external diseases through the smart deep learning architecture.

III. MATERIALS AND METHODS

Fig. 1 highlights the working procedure of the proposed architecture.

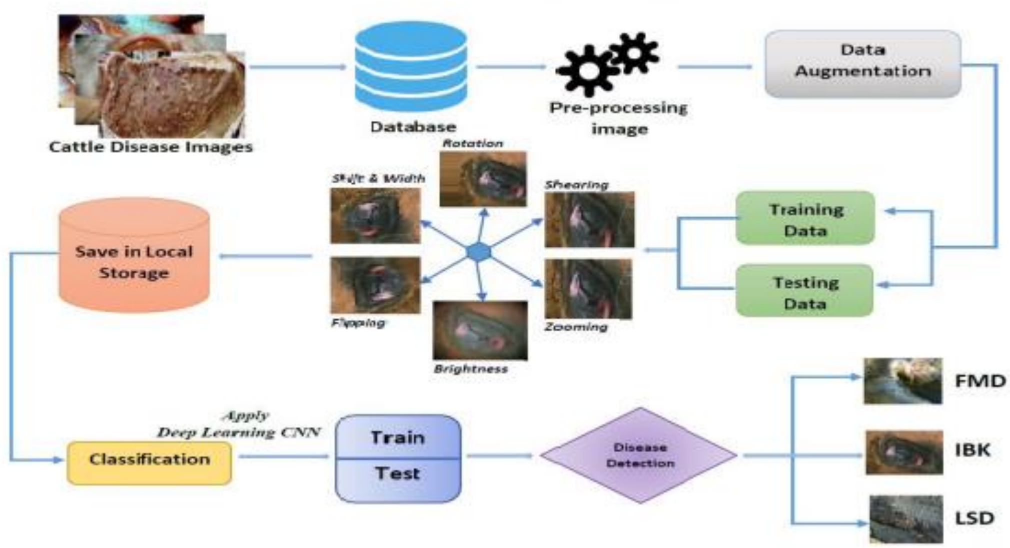

Fig. 1. The proposed model working architecture.

A. Dataset

The biggest challenge of this research was collecting data. The data was managed by several places like veterinary hospitals, cattle farms, the internet, and so forth The data was validated by veterinarians. The total number of raw images is 600 with three classes e.g. FMD, LSD, and IBK, and distributed respectively 250, 200, and 150 for each class. The images are resized by 32*32 pixels for CNN, 224*224 pixels for VGG-16, and 299*299 for Inception-V3, and all the images are in RGB format with a scale from 0-255. The training dataset contains 480 images and the testing dataset contains 120 images [16].

Table I represents the total images of the cattle disease dataset and there are 6000 images in the Dataset.

FMD IBK LSD

Fig. 2. External lesions of cattle diseases.

Fig. 2 shows that the visual signs of three external threaten diseases such as FMD, LSD, and IBK.

TABLE I. TOTAL IMAGES OF CATTLE DISEASES IN DATASET

Diseases	Number of raw images	Number of raw and augmented images	Number of Training images	Number of Testing images
FMD	250	2500	2000	500
LSD	200	2000	1600	400
IBK	150	1500	1200	300
Total	**600**	**6000**	**4800**	**1200**

Table II contains the visual symptoms of three mainstream diseases.

TABLE II. THE VISUAL SYMPTOMS OF CATTLE DISEASES.

Diseases	Visual Symptoms
LSD	It displays lumps and swelling and sores on the cattle skin.
FMD	It shows sores on the mouth and tongue of cattle and deep lesions on the feet.
IBK	It shows a tiny low opaque space on the membrane and membrane lesions are normally central in location on the eye.

B. Data Augmentation

Data augmentation is compulsory in deep learning neural networks especially when the dataset has fewer data. Hence, it helps to increase the dataset and removes over-fitting, and regularized the dataset. There are several data augmentation techniques such as shifting, resizing, rotating, flipping, shearing, zooming, and transforming brightness and contrast enhancement [17].

This model has used Keras library which has a class called ImageDataGenerator for augmenting data. Table III shows that several types of Data Augmentation techniques using the Keras library.

TABLE III. DIFFERENT TYPES OF DATA AUGMENTATION TECHNIQUES.

Augmentation Images	Augmentation techniques
 (Original image)	Load original image.
 (Rotation 90°)	datagen = ImageDataGenerator(rotation_range=90)
 (Flipped)	datagen = ImageDataGenerator(rotation_range=180, horizontal_flip=True)
 (Shift width and height)	datagen = ImageDataGenerator(width_shift_range=0.3, height_shift_range=0.2)
 (Shearing and zooming)	datagen = ImageDataGenerator(shear_range=0.5, zoom_range=0.6)
 (Brightness enhancement)	datagen = ImageDataGenerator(brightness_range=[0.1,0.3])

C. Convolutional Neural Networks Architecture

CNN is a type of feed-forwarding neural network that comprises convolutional or parallel calculation through a deep configuration [18]. It is a strong network that utilizes filters to extracting features from pictures. CNN's architecture was motivated by the type of neurons of the human brain that enables it to retrieve necessary information from pictures in comparison to conventional feed-forwarding neural networks [19]. The parameters of the layers containing some of the trainable filters (or kernels) that maintain a territory with a small capacity but enhanced throughout the entire depth into the input density [8].

CNN plays an important role in several sectors like image segmentation, classification, recognition, and so forth. In this proposed architecture, CNN was selected to identify the cattle disease image dataset since it has achieved modern image recognition. CNN has two primary sections: Feature Extraction and Classification. Feature extraction has pooling and convolution layers where classification has a fully connected layer [20, 21].

Convolutional Layer: Convolutional Layer is the first layer of traditional CNN that extracts the feature of the input images. In this layer, it's calculating the output into the neurons that are connected with local territories. Each filter is determined by multiplying regions and weights. In these datasets, each image size with 32×32 pixels width and height, and the depth is 3 (because it is an RGB channel) [22]. Feature vector would be produced by single or multiple convolutional layers respectively. Every layer contains several numbers of kernels or filters. These filters are convolved to input images. So, depth on the produced feature map $K_{i,j}^{(n-1)}$ is proportional to the total number of kernels comprised of the convolution activities [8]. The eq.1 is delivered in this model for convolution operation are,

$$X_i^{(n)} = \sum_{j=1}^{a_i^{(n-1)}} K_{i,j}^{(n-1)} * X_j^{(n)} + b_i^{(n)} \tag{1}$$

Here, the N^{th} convolution layer using bias b, as the output of $X_i^{(n)}$, K is considered as kernels.

Pooling Layer: The pooling layer used after the convolutional layer is to gather features from maps created by convolving a filter over an image. Usually, its function is to reduce the number of parameters, in other words, reduces the computational cost in the network. 2×2 (two by two) pixels used in this study with a stride size of 2 pixels which means that the pooling layer will progressively decrease the dimension of every feature map by a factor of 2 [23].

GoogleNet, etc. Fully Connected Layers are also important for non-linear combinations so that the output can be combined with the flat part of the output. CNN and Fully Connected Layers provide the same type of output when it was replaced [25].

Softmax: Softmax function recognizes the object between 0 and 1 using the probability theory [26]. It's mainly utilized for multi-class identification. It is applied on the output layer by eq.4

$$x_i^{(n)} = f(v_i^{(n)}), \tag{4}$$

$$\text{Where,} \quad v_i^{(n)} = \sum_{i=1}^{u_i^{(n-1)}} z_{i,j}^{(n-1)} x_i^{(n-1)}$$

Here, $z_{i,j}^{(n)}$ are the weights that are performed by the Fully Connected Layer to classifying the three mainstream external cattle diseases and f is referred to as a transfer function that is showing the nonlinearity [8].

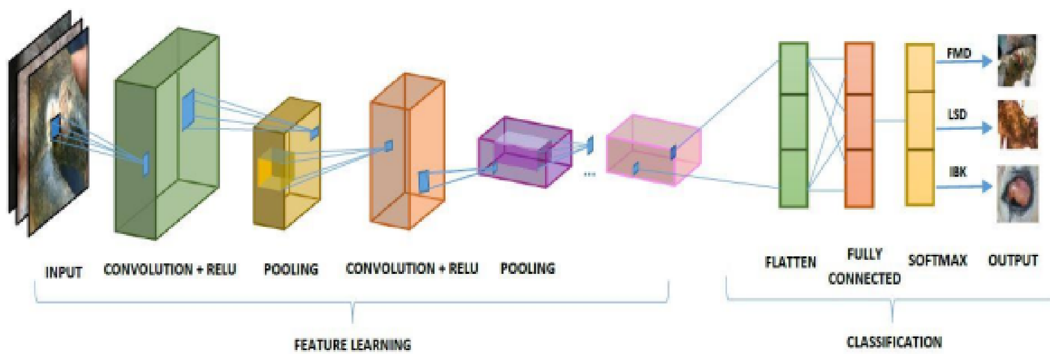

Fig. 3. The architecture of the CNN.

Fig. 3 represents the 3d architecture of the CNN algorithm.

ReLU: The Rectified Linear Unit(ReLU) is the most widely used activation function for hidden layers of NN(Neural Network). It overcomes the limitations of the Sigmoid function as it was only used for binary classification. ReLU handles this problem and mostly used for multi-class classification of image recognition. It performs the non-linear operation and reduces the vanishing gradients [24]. By doing the convolution layer on the cattle image dataset, ReLUs in eq.3 would be applied for the nonlinear operation of this outputs to $X_i^{(n)}$ in eq.2.

$$R_i^{(n)} = R\,(X_i^{(n)}) \tag{2}$$

$$R_i^{(n)} = \max\,(0,\ R_i^{(n)}) \tag{3}$$

Fully Connected Layer: By Fully Connected Layer (FC Layer) we usually mean that the inputs of all the levels will be connected to each activation unit. The last layers are very coherent which takes data from the first layers and compiles accurate output from it. Several CNN forms use Fully Connected Layers within the ILSVRC such as VGG, AlexNet,

D. *VGG-16*

VGG-16 is a CNN architecture which is developed by the Visual Geometry group. By using it, the ILSVR or ImageNet competition has won in 2004. It is weighted to be the best vision model masonry until the current date. It has 16 layers of its own CNN. In VGG-16, Smaller convolution layers come together to form a larger layer, which improves the efficiency of this layer [9]. Fig. 4 shows the VGG-16 architecture. The Convolutional layer denoted as Conv and

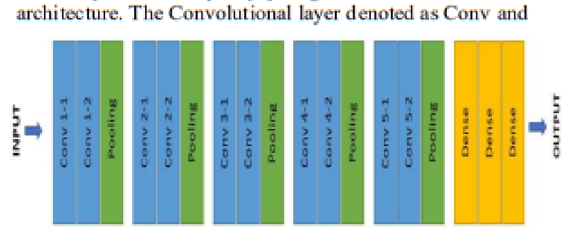

Fig. 4. The architecture of VGG-16.

the image size should be 224*224 pixels.

E. *Inception-V3*

Inception-V3 is a pre-trained model and broadly-used image recognize model which shown to achieve better accuracy on the ImageNet dataset. It usually focuses on computational power by modifying previous induction architecture. It has 42 layers. Compared to VGG, the

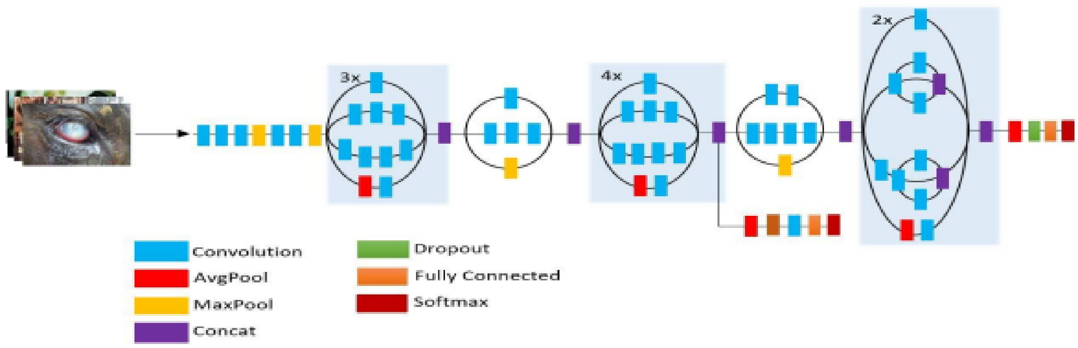

Fig. 5. The architecture of Inception-V3.

calculated efficiency of inception is much higher in computing resources and parameters. By refining the genuine Inception Network model by announcing factorized convolutions along with broad filter size, unbalanced convolutions, and factorization into lesser convolutions [10]. Fig. 5 shows that the architecture of Inception-V3 and it performs better than traditional CNN and VGG-16 architecture because it has 24 million parameters and the image size must be 299*299 pixels [27].

IV. Identification Of Performance Assessment

The progress of the classification model with seven evaluation metrics. The assessment of the metrics are stated as below [28]:

- Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
- Precession = $\frac{TP}{TP+FP}$
- Sensitivity = $\frac{TP}{TP+FN}$
- Specificity = $\frac{TN}{TP+FP}$
- Error rate = (1- Accuracy)
- F1-score = $2\times\frac{Precession \times Sensitivity}{Precession + Sensitivity}$
- G-mean = $\sqrt{(Sencitivity \times Specificity)}$

Here, TP (True Positive), FP (False Positive), TN (True Negative), and FN (False Negative).

V. Results And Discussion

Python Keras is the most used libraries that implements to recognize supplementary tasks. The model has used three well-known CNN technologies e.g. traditional CNN, VGG-16, and Inception-V3. Hence, the Inception-V3 has achieved the highest score among the tested algorithms. The training and the testing accuracy have achieved respectively 98% and 95% in Inception-V3 for Cattle Diseases Detection.

Fig. 6, Fig. 7, and Fig. 8 represent the confusion matrix of the proposed model. It shows that the Inception-V3 gets the highest results of the predicted label against the true label.

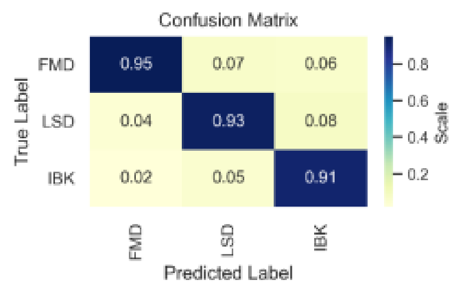

Fig. 6. Confusion matrix for CNN model.

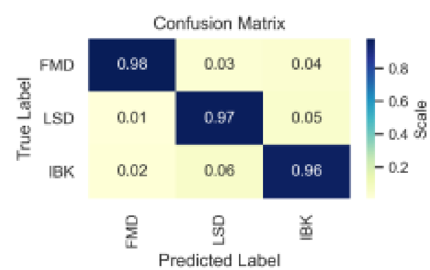

Fig. 7. Confusion matrix for Inception-V3 model.

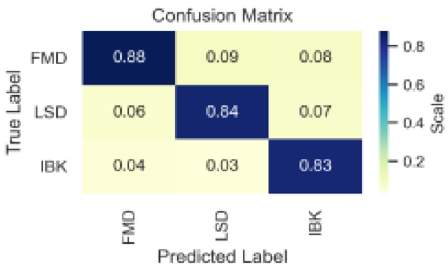

Fig. 8. Confusion matrix for VGG-16 model.

TABLE IV. DIFFERENT TYPES OF CLASSIFICATION RESULTS.

Evaluation Matrix	CNN	Inception-v3	VGG-16
Accuracy	92%	**95%**	91%
Precision	90%	**93%**	87%
Sensitivity	90%	**93%**	89%
Specificity	94%	**96%**	94%
G-mean	92%	**94%**	90%
F1-score	91%	**92%**	86%
Error rate	8%	**5%**	9%

Table IV shows the several types of classification results which are calculated by some evaluation matrix e.g. Accuracy, Precision, Sensitivity, Specificity, G-mean, F1-score, and Error or misclassification rate of CNN, Inception-V3, and VGG-16 model. Comparatively the Inception-V3 scored the maximum results.

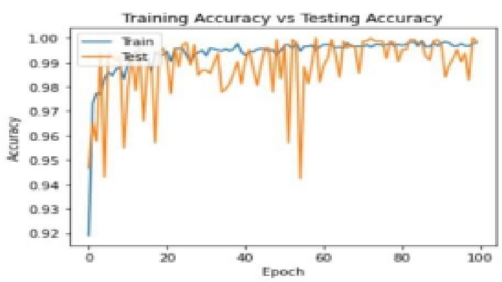

Fig. 9. Training Accuracy vs Testing Accuracy of Inception-V3.

Fig. 9 shows that the training accuracy is increasing smoothly with the iteration time.

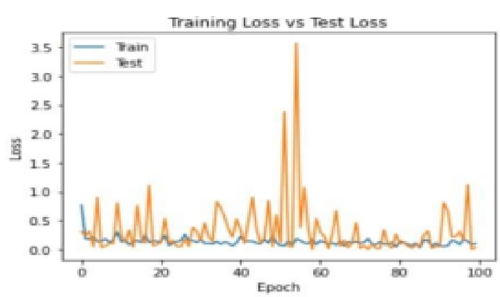

Fig. 10. Training Loss vs Testing Loss of Inception-V3.

Fig. 10 shows that the testing loss is decreasing with the iteration time are increased. The model was tested on 100 iterations and after 52 iteration time, the unexpected loss happened but then it decreased again at the increase of iteration.

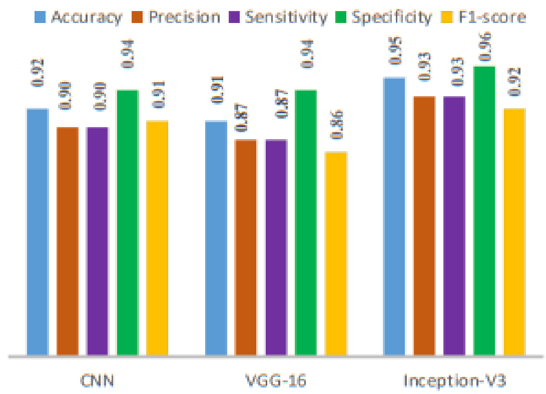

Fig. 11. Bar chart of the performance of CNN, VGG-16, and Inception-V3.

The comparison of the performance of CNN, VGG-16, and Inception-V3 are shown in Fig. 11.

VI. CONCLUSION

In this study, the external diseases of cattle are detected and classified using deep learning techniques e.g. CNN, VGG-16, and Inception-V3. The highest expected result was obtained from Inception-V3 among all the applied algorithms. It shows 93% sensitivity and 96% specificity. By testing the datasets, the classification of the disease has improved appropriately and given recognition. The transfer learning techniques are helping to increase the accuracy of the proposed model. The limitations of this paper are the less amount of raw data and for this reason, the accuracy is decreased and the loss is increased at a sudden time of iterations. Inadequate information and scarcity of precise diagnosis can lead to failure to give accurate results. We are also interested in working with internal and other external major diseases in the future. This research will help farmers at all levels to quickly detect external epidemic diseases of cattle and receive treatment at an early stage.

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