Cow Disease Recognition Using Convolutional Neural Network

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering.

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APPROVAL

This Project/internship titled "**Cow Disease Recognition Using Convolutional Neural Network**", submitted by Md. Mahfuzullah, ID: 181-15-11006 and Asif Bin Hasan, ID: 181-15-10686 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 4 January 2022.

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Md. Tarek Habib, Assistant Professor, Department of CSE,** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

In the South Asian region, cow illness is a regular occurrence. Every season, poor rural residents, as well as dairy farm owners, face the same issue. Dairy farming is a large and developing agricultural sector in Bangladesh - a country of South Asia. A large portion of the population relies on cattle for a living. Cow milk is a source of pure nutrition in Bangladesh hence cows provide the bulk of milk and meat. Every year, farmers lose a lot of money due to cow diseases. Cow diseases reduce the amount of milk and meat produced. Recognizing cow diseases has thus become a critical undertaking to be fulfilled. In recent years, deep learning has been gaining a lot of popularity because of its superior accuracy when trained with a lot of data. Using deep learning, we will develop a system to recognize cow diseases. We have begun by reading many online publications, journals, and relevant studies before heading out to the field to tour dairy farms and village habitats. Brucellosis, lumpy skin disease, foot & mouth disease, and mastitis diseases are the four most frequently occurring cow diseases in Bangladesh. Then we have collected pictures of both healthy and diseased cows. We have proceeded to our dataset with five classes after gathering all of the picture data. To recognize cow diseases, we have used three deep learning pre-trained models with our dataset. We have achieved satisfactory results with the MobileNetV2 by attaining accuracy of 95.43%. For this study, we have also used two more pre-trained models, Alexnet and VGG16 which exhibit the accuracy of 86.27% and 90.85% respectively. The MobileNetV2 has not only performed the best in terms of accuracy but also some other indicative performance metrics like sensitivity, specificity, and precision. This research can help us recognize cow diseases quickly and avoid the unexpected loss of our livestock. As well, it also has a bright future in both the domestic and international markets.

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CHAPTER 1

Introduction

1.1 Introduction

Deep learning is nowadays getting very popular as well as demanding [1]. It gains its popularity within a short period of time as it is a younger field in the AI family. Basically, Deep Structured Learning works according to the method of Artificial Neural Network which is inspired by complicated brain functions and structure. The algorithms of deep learning are so strong that computers can read images in the blessing of deep learning. A common problem that arises first is to work with a huge amount of data, deep learning solves that problem. It can deal with a large amount of data. Moreover, it can solve many real-life problems through its advanced algorithm. Deep learning algorithms must be carefully trained and evaluated using data in order to find the best answer for a certain problem.

In Asia, Cow is a common animal. Especially, in the southern side of Asia, there are a lot of rural areas where people used to raise the cow as their pet animal as well as their business interest. Many family's economies directly or indirectly depend on cows in this region. Even in our country, cattle farming is a good business activity. There are about 2.85 cr cows in our country [2].

Among that number about 2,76,58,488 were found in the rural areas. It seems that cow farming is a profitable field but there is a barrier in the field and it's the diseases of the cows. Quick treatment is easy to obtain in a city, but it is difficult to obtain treatment in a rural region. People in rural areas are unprepared for unexpected events. They have no idea how to deal with cattle ailments and have little knowledge of necessary activities. As a result, many cows in our country die each year from various diseases. This problem can be managed if diseases can be detected early enough. This can be obtained by utilizing an online computer vision-based expert system capable of detecting illnesses in cows from a smartphone image. By using the system cow owners can detect the diseases quickly and can be benefited through proper treatment timely.

It will reduce the death rate of cows in our country as well as cow owners will be benefited from the system.

We've employed CNN, and it's now widely used in a variety of fields because of its superior performance [3]. To detect objects, distinguish faces, and so on, CNN uses image recognition and classification. CNN is typically used to classify images, cluster them based on similarity, and subsequently recognize objects. In recent years, CNNs have been widely employed in the detection of numerous skin diseases on human skin, cattle skin, and other animal skin [4].

1.2 Motivation

In the south Asian region, people's economy depends on agriculture. Almost four out of five people have involved themselves with agriculture in this country. In Bangladesh, dairy farming is a significant and promising agricultural sector. Approximately 20% of Bangladesh's population earns a living from livestock and poultry farming. Cows provide the majority of milk in Bangladesh. It fulfills the 90% demand for milk in our country [5]. In the years 2020-21 our country produces about 119.85 Lakh Metric Ton milk as well as 84.40 Lakh Metric Ton meat [6]. Cow disease is a great threat to this sector. Cows get attacked by diseases that cause a smaller amount of milk and meat production. On the other hand, cows lose their productivity after being attacked by the diseases. So, it is a great bother for the cow owner. Cow diseases are even more dangerous for dairy farm owners. Some diseases are contagious and often they cause the death of a large number of cows. This incident leads the farm owners to a huge amount of money loss. This financial loss can be prevented if the disease can be recognized to an early stage. The cow is our main source of milk and meat. It fulfills the demand of our country's people. So, to ensure a good production rate and a better future for the livestock resource we have found out that cow disease detection is an important task. We plan to use deep learning to recognize cow ailments because there isn't much research on the subject.

1.3 Objectives

In our research work, we choose the CNN model for recognizing cow diseases. We are able to use our smartphones in this research work for collecting data. We have had good fieldwork when collecting data from different places. As we mentioned above, there are a few research works on the topic. That is why working with cattle illnesses and deep learning approaches interests us. Our expert system will be able to detect diseases just on a smartphone photograph.

Deep learning is an area of machine learning that deals with artificial neural networks, which are algorithms inspired by the structure and function of the brain. Our world has been revolutionized by AI in the same way that electricity has. Deep learning gives researchers the ability to create more engaging and intelligent AI apps that can accomplish tasks without the need for human interaction. CNN's popularity is skyrocketing, and its outstanding performance has made it widely used in a range of fields. It has demonstrated great competence in the field of image recognition. CNN models are portable and may be deployed on any platform. We decided to employ CNN for disease identification in cows because CNN has been used in some amazing research.

1.4 Expected Outcome

Our research work will help those people who are involved in cow farming. It will help them to find out the diseases of cows and recognize them quickly. So that they can take initiatives early. For the successful recognition of cattle diseases, our trained CNN models will be applied in smart cloud-based apps. Using this cow owner can figure out the conditions of the cows easily and quickly. Ultimately it will help them to save their cattle with early treatment, besides Farmers who are not familiar cattle illnesses will also be benefited as well. Our research work will also reduce the risk of cattle death and unexpected Economic loss of dairy farms.

Bangladesh's ministry and other countries may work together to implement our approaches, which would help them enhance cattle production while keeping them healthy. This research will result in the publication of one or more publications in international conference proceedings or journals.

1.5 Report Layout

In this report, we proposed a CNN model to recognize the cow diseases, it contains six parts which are given as below:

Chapter 1: Introduction

We explain the introduction of the research work with its motivation, objectives, and expected outcome in this chapter.

Chapter 2: Background Study

In this chapter, we go through the literature review, research summary, problem scope, and challenges.

Chapter 3: Research Methodology

We address the workflow of this research, data collection procedure, implementation requirements in this chapter.

Chapter 4: Experimental Results and Discussion

This chapter covers the research workflow, data gathering procedures, and implementation prerequisites.

Chapter 5: Impact on Society, Environment, and Sustainability

This chapter explains how our research affects society and the environment.

Chapter 6: Conclusion

This chapter includes an overview of our studies as well as recommendations for further work.

CHAPTER 2

Background Study

2.1 Introduction

In this part, we will discuss the literature review, research summary, scope of the problem, and the difficulties we encountered while working on this chapter. In the literature review section, we will describe various research publications related to our study and explain the underlying algorithms, classifiers, and accuracies of their works. In the research summary section, we will describe the limitation of the previous research. In the scope of the problem section, we will discuss how our CNN models may help with the problem. In the challenges section, we will talk about the blockage we encountered during our research.

2.2 Literature Review

Using the traditional machine learning technique, some research work has been done to recognizing the related problem of various human, animal, and fruit diseases. As we know, on this topic a few research has been done. As well, many researchers recognize skin diseases like human skin, cattle skin, and other animals.

Gaurav Rai et al. used deep learning to detect lumpy skin diseases [7]. In their work, they have used 132 Lumpy skin diseases images and 199 Normal cow images. For better accuracy, they have used three different types of CNN models which are Inception-V3, VGG-16, VGG-19, and the accuracy of these models are 92.5%, 87.9%, and 88.2% respectively. In three models they have found the best accuracy from Inception-V3. They used some other methodology, which are KNN, SVM, NB, ANN, and LR.

Timothy Kudzanayi Kuhamba et al. used CNN to detect foot and mouth diseases [8]. Though foot and mouth diseases image data collection is challenging work, Still they have collected some useful data to train their models and six CNN models which are VGG16, Inception V3, DenseNet 201, Resnet V2, ResNet 50, and InceptionResnet V2 were trained to find out the best accuracy. After their work, they have achieved 93.75% accuracy from DenseNet 201 which is the best accuracy.

Rotimi-Williams Bello et al. used CNN to classify cows using body patterns [9]. They recognize the species of a cow from the body pattern of the cow image. In their research, they have used a dataset of 1000 cow images, and 10 species where each species has 100 images. After this work, they have achieved 92.59% training accuracy and 89.95% testing accuracy.

Xudong Zhang et al. used CNN to recognize dairy cow mastitis diseases [10]. They have applied a new algorithm EFMYOLOv3 (Enhanced Fusion MobileNetV3 You Only Look Once v3) which detect dairy cow mastitis from thermal images. Their proposed model is based on MobileNetV3 and it's a lightweight model. After their work, they have achieved 83.33% test accuracy.

Beibei Xu et al. classified and counted livestock by using CNN [11]. In photos acquired by quadcopters, they applied the Mask R-CNN method for feature extraction and training. This technique is evaluated using a real pasture surveillance dataset. In their research, they have used a dataset of 1000 images, where two different types of classes have been used, and this is cattle and sheep. After their research, they have achieved 96% test accuracy.

Md. T. Habib et al. recognize papaya diseases using computer vision-based nine types of classifiers algorithm [12]. They have used a dataset of 129 images where 84 images were used for training, and 45 images is used for testing. Their classifier algorithm are SVMs, C4.5, Naive Bayes, Logistic Regression, kNN, Random Forest, BPN, CPN, and RIPPER, and Accuracy of this algorithm are 95.2%, 86.67%, 77.78%, 75.91%, 71.11%, 90.36%, 89.58%, 91.66%, and 78.83% respectively. After their research, they have achieved the highest accuracy on SVMs which is 95.2%.

Nurul Akmalia et al. used local binary pattern (LBP) and CNN to classify skin diseases based on shape, color, and texture of human skin diseases [13]. The purpose of this work is the early detection of human skin diseases. Six types of human skin diseases have been used for this research. They have used a dataset of 72 images where 60 images were used for training and 12 images were used for testing. After their research, they have achieved an average of 92% accuracy.

Rashidul Hasan Hridoy et al. used some CNN models to recognize human skin disorders [14]. In their research, they have detected twenty types of skin disorders. A dataset of 52500 images has been used to recognize these twenty types of skin disorders where 42000 images were used for training, 4200 images were used for validation, and 6300 images were used for testing. They have used EfficientNet-B0 to B7 eight transfer learning model to find out the best accuracy. After their work, they have achieved in EfficientNet-B7 97.10% test accuracy which is the best accuracy among all over the models.

Rola EL SALEH et al. have used CNN to identify human face skin diseases [15]. There proposed model was VGG-16. A dataset of 12000 augmented images has been used for this research, which was generated from 2000 original images to identify 10 classes. Their image's pixel size was 224×224. After their work, they have achieved 88% accuracy from their model VGG-16.

Alvaro Fuentes et al. have used deep learning to perform hierarchical cow behavior recognition with spatio-temporal data [16]. Their study focuses on cow behavior and expands the notion of activity detection in video. Their framework combines frame-level appearance characteristics with spatio-temporal data that includes more context-temporal elements. Their system can recognize (classify) and locate (bounding box) locations in video frames that comprise various cow actions. They also present their cow behavior dataset, which contains films captured with RGB cameras on various livestock ranches during the day and night. The system can efficiently distinguish 15 various types of hierarchical activities separated into individual and group activities, as well as part actions, according to the results of this study.

2.3 Research Summary

There are some cattle skin diseases recognition and classification work already have been done by using machine learning, and data mining technique. Machine learning and deep learning technique are used to disease recognition increasing day by day. In the literature review section, we have already discussed several types of publications where they have worked to detect this kind of disease. Some researchers used prediction systems and traditional techniques. However, they are unable to reach sufficient precision. That's why their detecting method is unable to produce satisfactory results. As far as we know, no detection technique has been used to distinguish between a healthy class and four classes of cow diseases. After reading this type of research paper we have found that CNN has been used by some researchers to increase accuracy for other skin diseases.

2.4 Scope of the Problem

After reviewing several similar research papers, we discovered a common issue and the issue is their image dataset was not enough. The deep learning technique provides better accuracy when you have a huge image dataset. But they are using a few image datasets for their model that's why they can't get better accuracy and when they use new test images then their proposed system can't provide good results. Nowadays, a notable portion of the research community has been using deep learning to solve recognition problems and has used a big dataset to train their model. Their concept is compatible with contemporary technology, making their findings relevant and useful to the general public. As a result, we decided to use deep learning to train a model for recognizing cattle diseases. It will work with existing technologies and will benefit general people.

2.5 Challenges

During data collection, we have faced a lot of problems. We were collecting our data over the whole year. Some diseases are seasonal, so we had to wait for some time to collect data. Diseased cows are not available everywhere. That's why we had to visit many farms and animal hospitals searching for diseased cows. Taking pictures of cows when they are sick of giving birth is very risky. Cows often behave aggressively. We have collected data on these risks. In Fig 2.1 we show a picture of a cattle farm.

Fig 2.1: Cattle farm.

CHAPTER 3

Research Methodology

3.1 Introduction

The major purpose of this study is to develop a model that will be able to correctly recognize cow diseases in less time. Another goal of this study is to assist persons who are involved with cattle. In this study, CNN was utilized. In addition, we used two pre-trained models. The full strategy of our study work is depicted in Fig. 3.1.

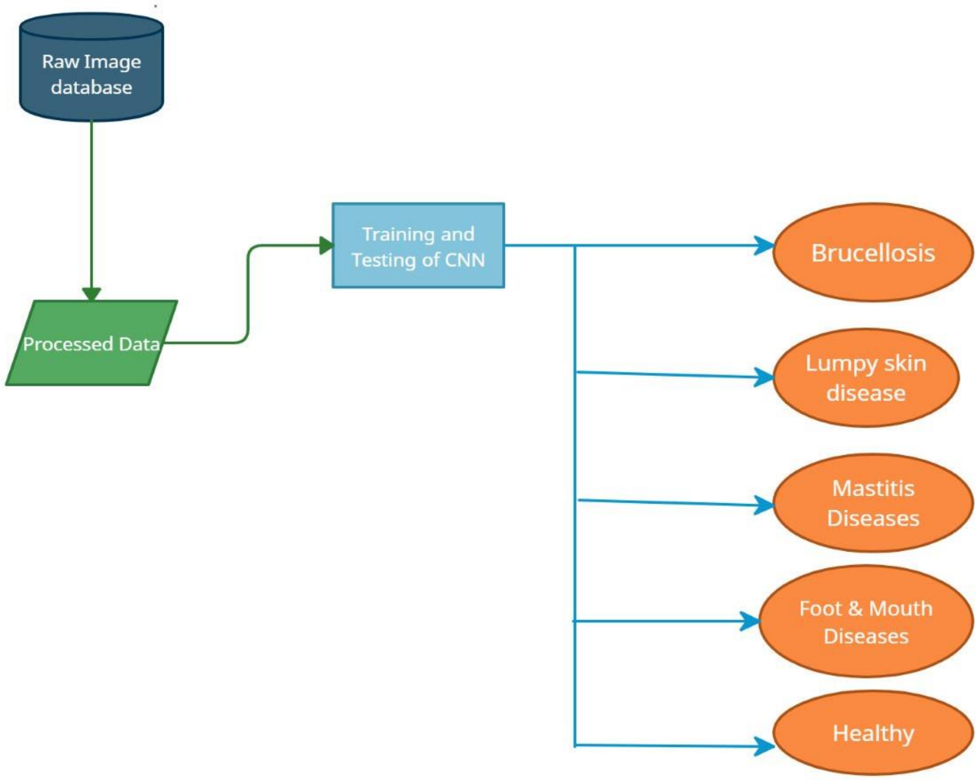

Fig. 3.1: Block diagram of this research methodology

The phases of working on this research project are depicted in a block diagram. Any research project's most important component is the dataset. Before we started taking pictures, we did a lot of research on cattle ailments. Following that, we gather photos from numerous sources. We briefly describe the disease description and data-gathering techniques in this chapter. In this chapter, we'll go through all of the theoretical information.

3.2 Disease description

Disease research is an important aspect of our research. It makes it simple to comprehend the consequences of many types of cattle illnesses on cattle. Following the illness analysis, we discovered four frequent cow diseases in Bangladesh: Brucellosis, Lumpy skin disease, Foot & Mouth Diseases, and Mastitis Diseases.

3.2.1 Brucellosis

Brucellosis is a chronic bacterial infection . The disease is caused by various bacteria of the family Brucella. It is a zoonotic disease, it can also affect humans. This disease is very common in domestic animals. (Ex: cows, goats, sheep). Cattles are infected by one of the Brucella species named *B.abortus* [17]. The bacteria can enter into the body of cattle by broken skin, coitus, or through the conjunctiva. The infected animal doesn't show any symptoms. But some possible symptoms are swelling of the testicles in ox and occasionally the bacteria localize in the joints causing arthritis. But if any human is affected by this disease, he /she can have a fever, headache, weakness, weight loss etc.

3.2.2 Lumpy Skin Disease

Lumpy skin disease is a disease caused by a virus [18]. The virus that is responsible for this disease is named the Lumpy skin disease virus. The virus is from the Capri pox virus genus and the family is Poxviridae. This disease is only found in cattle. This virus can enter the body by blood-feeding arthropods such as mosquitos, flies etc. Repeated use of needles is another reason for the disease. It can spread through blood, saliva, ocular and nasal discharges and semen. The infected cattle show some symptoms when affected by this disease. The affected cow will have a fever, Appetite decreases, Saliva comes out through the mouth and nose, legs are swollen, skin lesions, anorexia nervosa, etc.

3.2.3 Foot & Mouth Diseases

Foot & mouth disease is a contagious viral disease. Coxsackievirus is the reason for this disease. It has seven types [19]. But Coxsackievirus A16 is mainly responsible for infecting the cattle. This disease is very serious in our countries. The disease has no particular treatment so the death rate is so high. The symptoms of the disease are fever, depression, not eating or difficulty eating, milk production decreasing, increased salivation, blisters in the body, and lesions on the mouth, muzzle, and feet. This disease is so dangerous that it can cause sudden death to calves. This disease is spread very quickly through direct contact with the infected animal. The virus can be passed through water, hey, milk, urine etc. This virus can spread through the air when it is windy.

3.2.4 Mastitis Diseases

Mastitis disease is a disease that infects the udder tissues [20]. The reason for this disease is microorganisms. The microorganisms are viruses, bacterias, fungus as well as mycoplasma. In most cases, we can find that bacterias are mainly responsible for this disease.In 70% of cases, we can see the bacteria is infected. The bacterias are Pasteurella multocida, E.coli,Leptospira Pomona,Str. agalactiae,Brucella abortus, etc.The disease can be spread through unhygienic food distribution. Injury to the mammary reason can also be a reason for this disease. The symptoms of this disease are very clear. They have increased body temperature, sunken eyes, the watery appearance of milk, swelling, and redness of the udder, due to pain the mobility of infected cows is reduced.

3.3 Data Collection

For us, gathering data is the most difficult endeavor. Following the disease investigation, we went to some dairy farms and villages to capture pictures of cattle's pictures. We gathered photos throughout the year to create a more comprehensive dataset for our research, as seasonal changes have an impact on cattle diseases. Cattle illnesses developed dramatically during the rainy and cold seasons.

3.4 Dataset Description

We focused on the dataset because it is the most important component of a good model. Some pictures could not be understood due to noise while taking pictures, while some unexpected pictures were caught. We had to filter it for more accuracy. It will take us a few days to create a more comprehensive dataset. We employed a total of 3083 cow photos in our study, which were classified into five classes. Color photographs have been utilized in all of our processes. In our research, we selected photos with resolutions of 224 × 224 and 227 × 227 pixels. Table 3.1 shows the distribution of the collected dataset by class.

Table 3.1: The distribution of the photographs collected by class.

Class	Frequency
Healthy	1354
Brucellosis Diseases	250
Mastitis Diseases	411
Lumpy skin disease	585
Foot & Mouth Disease	483
Total	**3083**

We reshaped all photos using Pillow to 224×224, 227×227, and reduced the quality of all photographs. Pillow is a program that can access, manipulate, and save a variety of picture file formats. It's a Python programming language library that's available for free. The images of Brucellosis diseases, Mastitis diseases, Lumpy skin disease, Foot & mouth disease, and Healthy cow are shown below Fig. 3.3, Fig. 3.4, Fig. 3.5, Fig. 3.6, and Fig. 3.2 respectively.

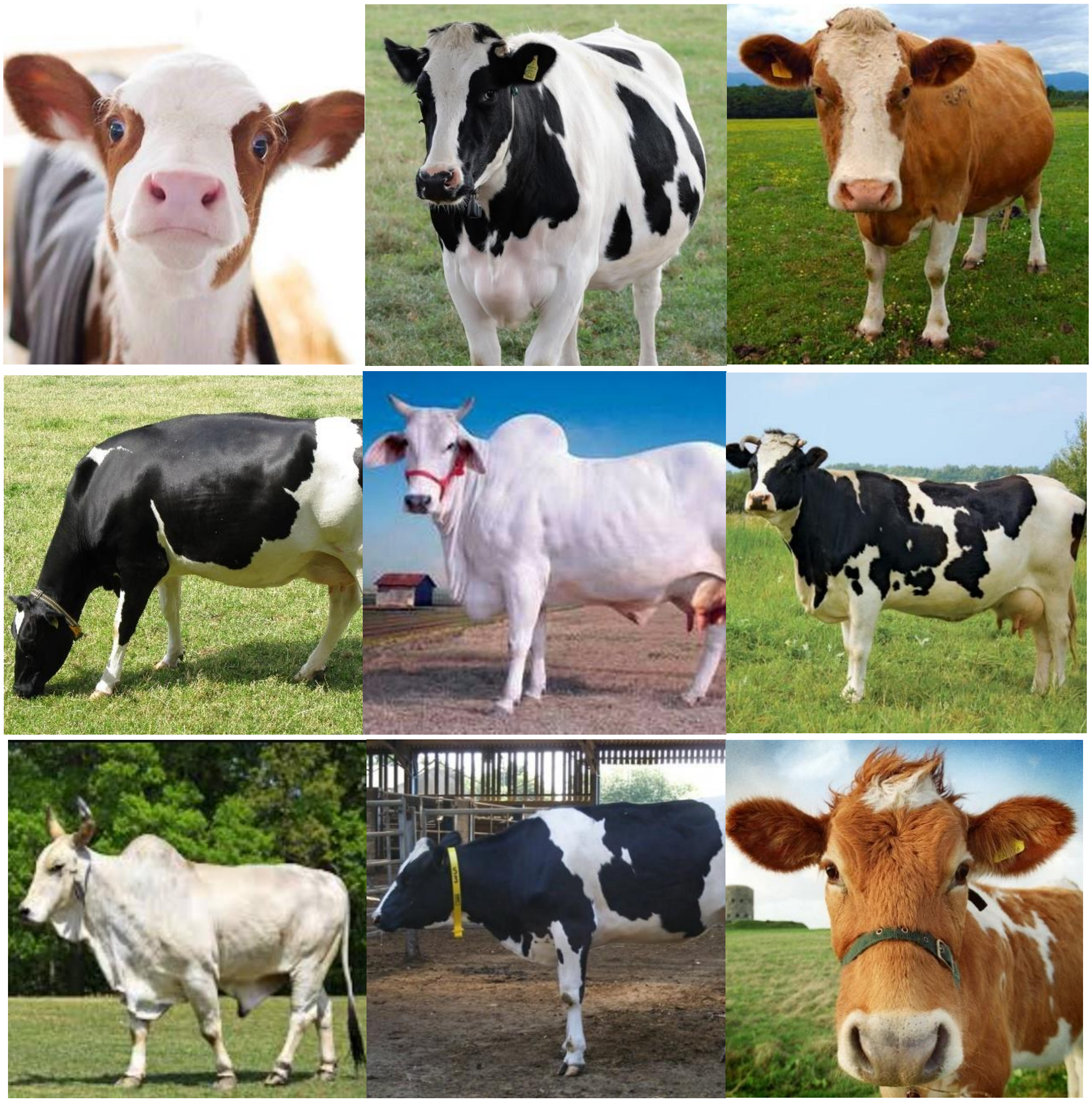

Fig. 3.2: Healthy cow

Fig. 3.3: Brucellosis

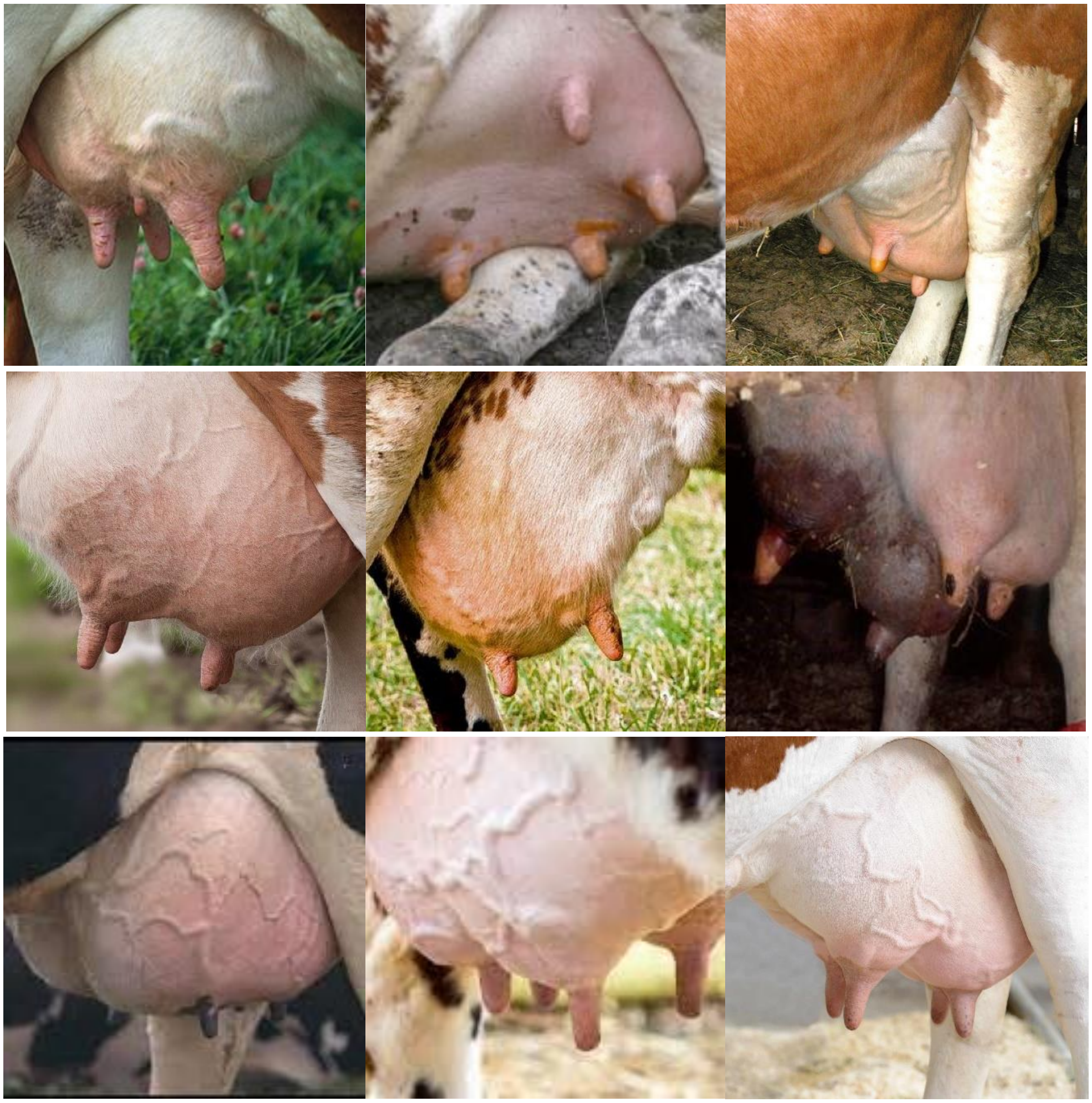

Fig. 3.4: Mastitis disease.

Fig. 3.5: Lumpy skin disease

Fig. 3.6: Foot & Mouth disease.

3.5 Statistical Analysis

We have a total of 3083 photos of cows from various locations. We took 1729 pictures of the sick cows and 1354 pictures of healthy cows. In Fig. 3.6, the number of afflicted and healthy cow photos is presented. There are 585 lumpy skin diseases, 483 foot & mouth diseases, 250 brucellosis diseases, and 411 mastitis diseases among the 1729 photographs that are affected. Fig. 3.7 shows percentage of affected and healthy images.

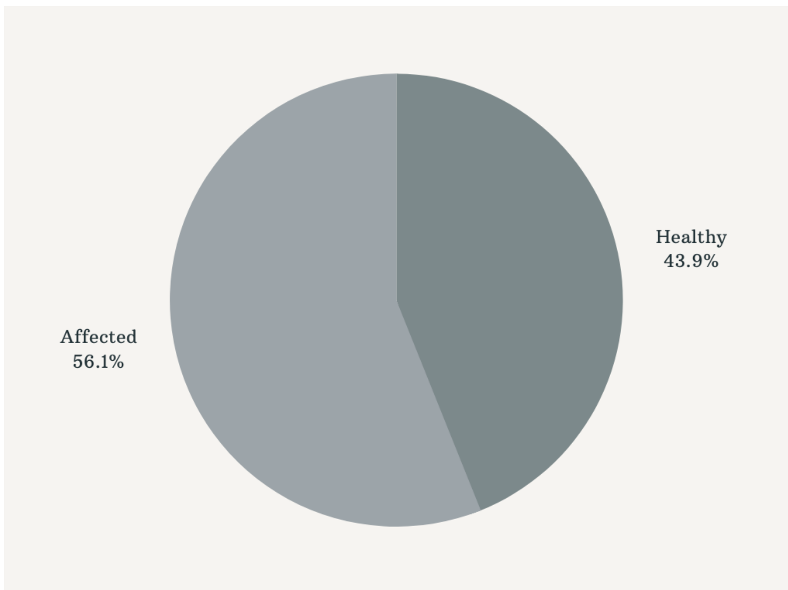

Fig. 3.7: Percentage of affected and healthy images.

Fig. 3.8 shows percentage of lumpy skin diseases, foot & mouth disease, mastitis diseases, brucellosis diseases, and healthy images.

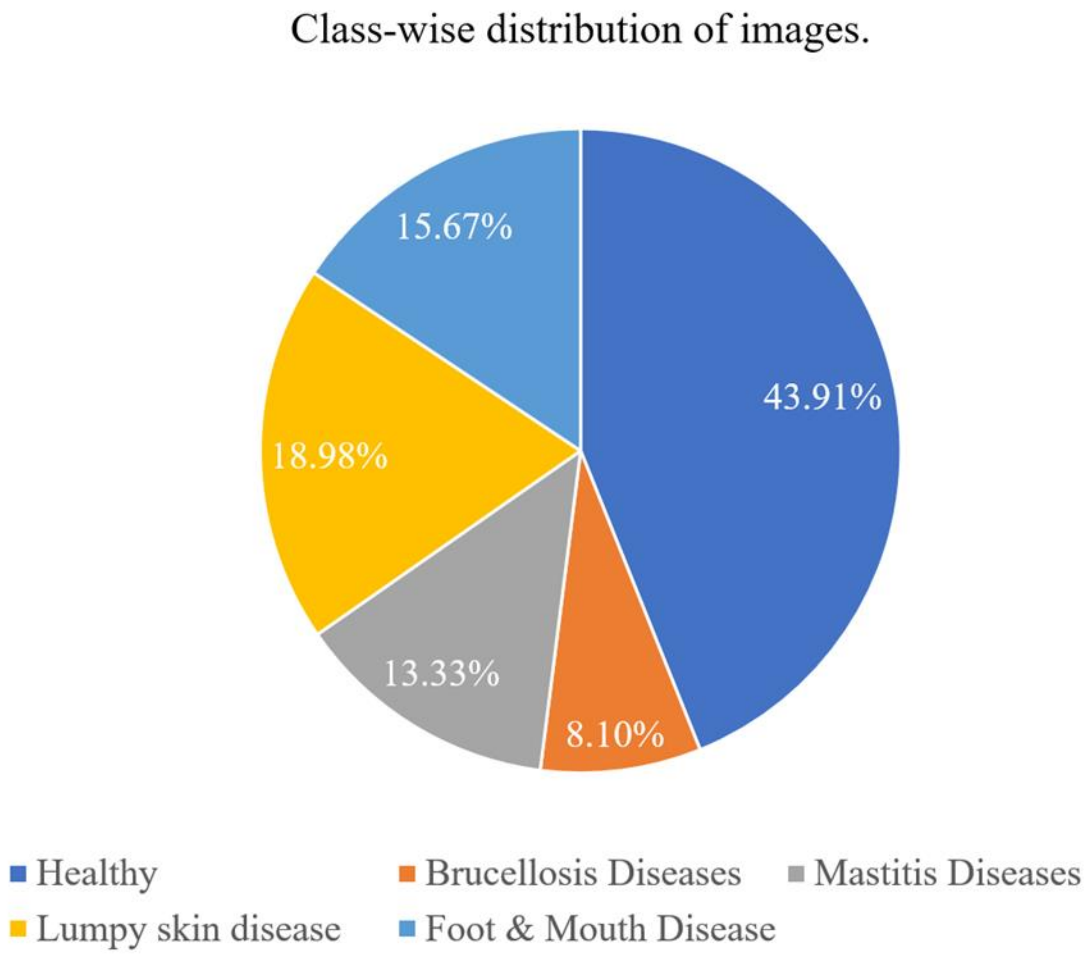

Fig. 3.8: Percentage of lumpy skin diseases, Foot & mouth disease, Mastitis diseases, Brucellosis diseases, and healthy images.

3.6 CNN Model for Disease Recognition

CNN is likely the most common deep learning architecture in recent years. CNN's popularity is growing by the day due to its effectiveness and enormous success. Because of the advent of AlexNet, interest in CNN began to expand after 2012. These days, CNN's are frequently utilized for image segmentation, classification, and recognition. The fundamental rationale for utilizing CNN is to analyze many sorts of data, such as signal data and time series in 1D, pictures or audio signals in 2D, and video in 3D. CNN is currently widely utilized. In our investigation, we used CNN since it is more effective and performs better than other algorithms. CNN is now being used by researchers to solve a variety of challenges. CNN models, on the other hand, can run on any device. It also does parameter sharing and uses specific convolution and pooling algorithms, making them universally appealing. During feature extraction, CNN can lower the image dimension without sacrificing features.

Feature extraction and classification are two crucial components of CNN. During the image categorization, a series of convolutional, pooling, and fully connected layers are used. Convolution and pooling layers are used for all feature extraction operations, whereas fully connected layers are used for classification. For feature extraction, input images are routed through the convolutional layer. Softmax is used for multiclass classification tasks to normalize the output of the neural network. The input layer, hidden layers, and output layer are three different types of layers in CNN.

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

In concern of good accuracy, we collect a lot of images from the beginning of the work. We have moved many places and collected as many images as we can to enrich our dataset. To save our dataset and model, we employed cloud-based storage. We used CNN in our research work so that we can train a model that can recognize diseases of cows. We proposed MobileNet V2 as our used model in this research, we get good accuracy in the end after using it. As our main concern is accuracy, we keep focusing on the dataset throughout the research work. We will briefly summarize the results of our experiment in this chapter.

4.2 Experimental Results & Analysis

The research is carried out using a dataset of 3383 images divided into five classes. To train our models, we used Google Colab. In this study, we employed 33 convolutional filters in the model. We've talked about this model briefly in the parts below, along with other related material.

4.2.1 AlexNet

The ILSVRC 2012 competition was won by AlexNet by a significant margin [21]. One of the most straightforward approaches is AlexNet CNN. Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever formed the SuperVision group, which created it. 227x227 pixels images is required for AlexNet model input. It has five convolutional layer and three fully connected layer where final layer is softmax. Convolutions, max pooling, dropout, data augmentation, ReLU activations, and SGD with momentum were all used. Every convolutional and fully-connected layer had ReLU activations tied to it. Fig. 4.1, shows the AlexNet architectural map.

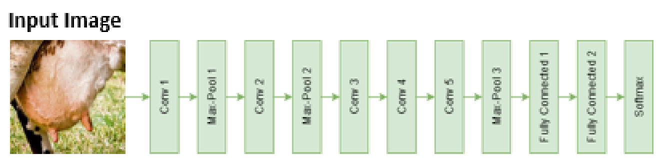

Fig. 4.1: Architecture map of AlexNet.

In Fig. 4.2, shown the plot graph of AlexNet.

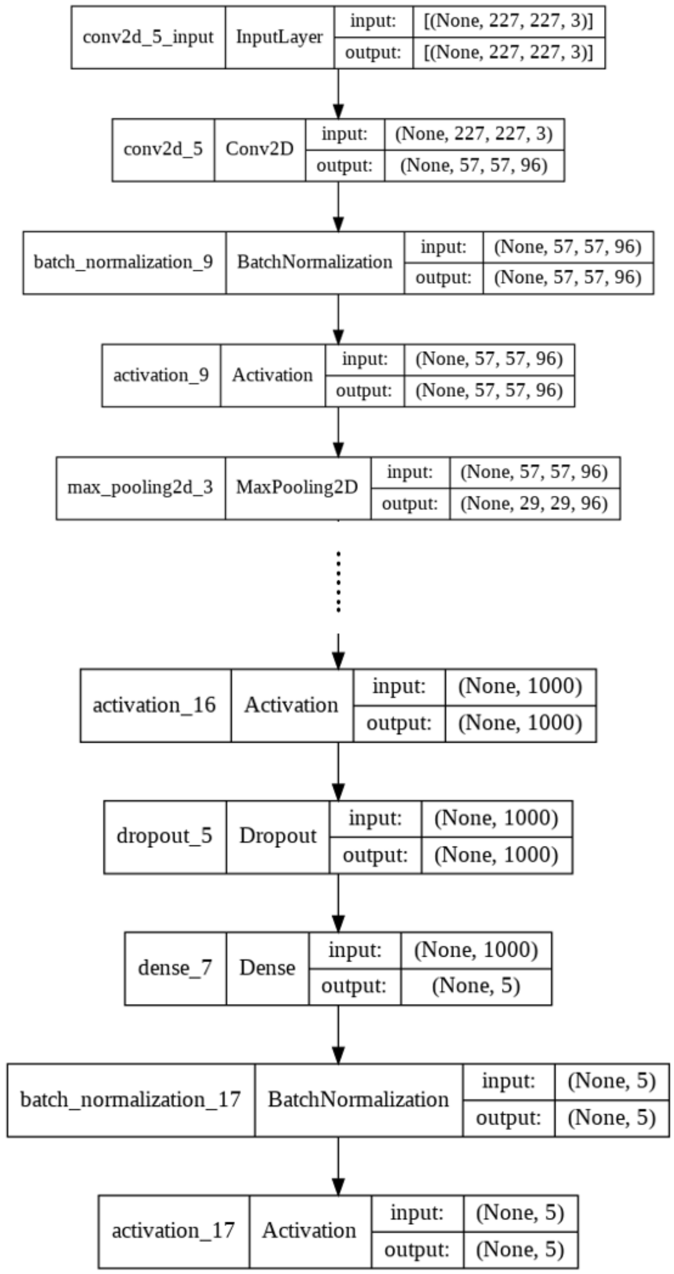

Fig. 4.2: Plot graph of AlexNet.

After using AlexNet in this research, we can't get a satisfactory result. We have achieved 87.24% training accuracy, 86.80% validation accuracy, and 86.27% test accuracy. In Fig. 4.3, accuracy chart of AlexNet.

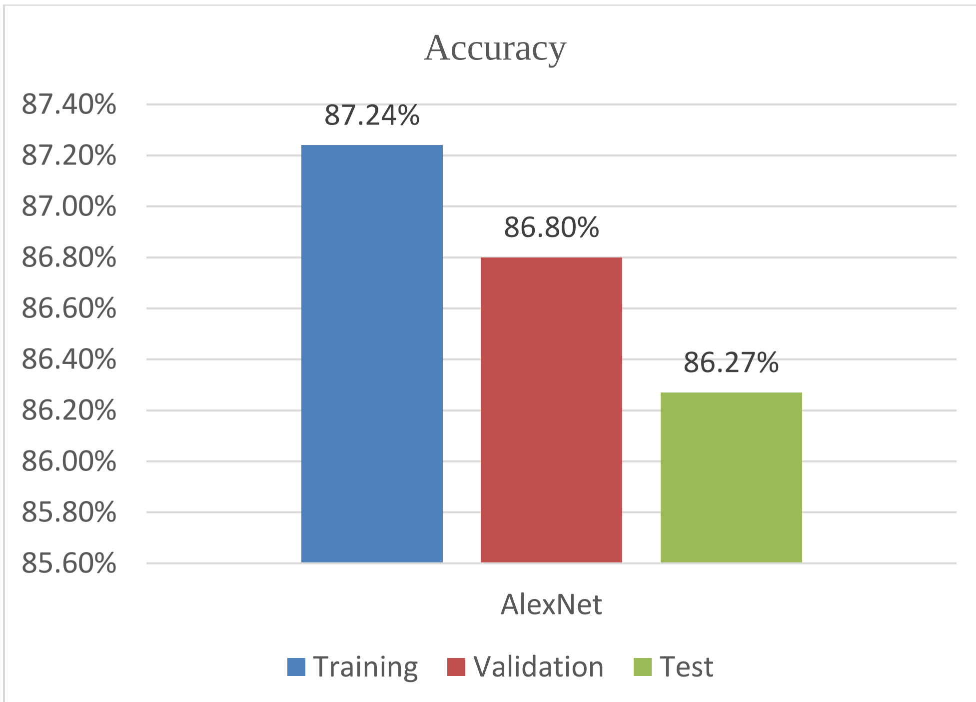

Fig. 4.3: Accuracy chart of AlexNet.

AlexNet has a total of 28,084,757 parameters in its final layer. There are 28,063,621 trainable parameters and 21,136 non-trainable parameters in this model. The AlexNet model overview is shown in Fig. 4.4.

```
 dropout_1 (Dropout)         (None, 4096)              0

 batch_normalization_6 (Batc  (None, 4096)             16384
 hNormalization)

 dense_3 (Dense)             (None, 1000)              4097000

 activation_7 (Activation)   (None, 1000)              0

 dropout_2 (Dropout)         (None, 1000)              0

 batch_normalization_7 (Batc  (None, 1000)             4000
 hNormalization)

 dense_4 (Dense)             (None, 5)                 5005

 activation_8 (Activation)   (None, 5)                 0

=================================================================
Total params: 28,084,757
Trainable params: 28,063,621
Non-trainable params: 21,136
_________________________________________________________________
```

Fig. 4.4: Model summery of AlexNet.

4.2.2 VGG16

VGG16 is a CNN architecture that won the ILSVRC-2014 competition, with 138 million (approximately) parameters [22]. It contains 16 layers and an input layer that accepts pictures of 224 224 pixels. Using NVIDIA Titan Black GPUs, this model was trained on 14 million photos. K. Simonyan and A. Zissermantrained introduced the VGG16 model. In all of the convolution layers in stride 1, this architecture employed three filters. It employed three completely linked layers, the first two of which used ReLu activation and the third of which used softmax. Fig. 4.5, shows the VGG16 architectural map.

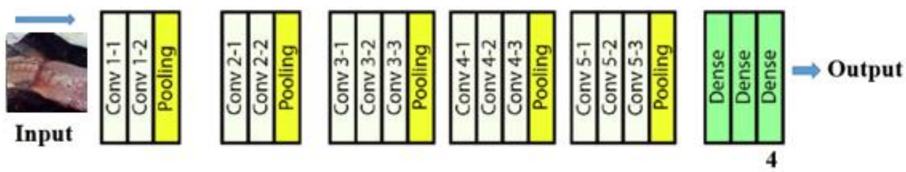

Fig. 4.5: Architecture map of VGG16.

In Fig. 4.6, shown the plot graph of VGG16.

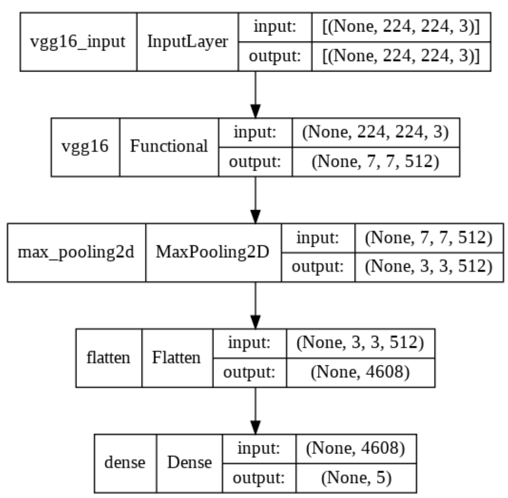

Fig. 4.6: Plot graph of VGG16.

VGG16 has also performed impressively in the classification of images of all classes. We have achieved 91.53% training accuracy, 90.48% validation accuracy, and 90.85% test accuracy after 45 epochs using VGG16. In Fig. 4.7 shown the accuracy chart of VGG16.

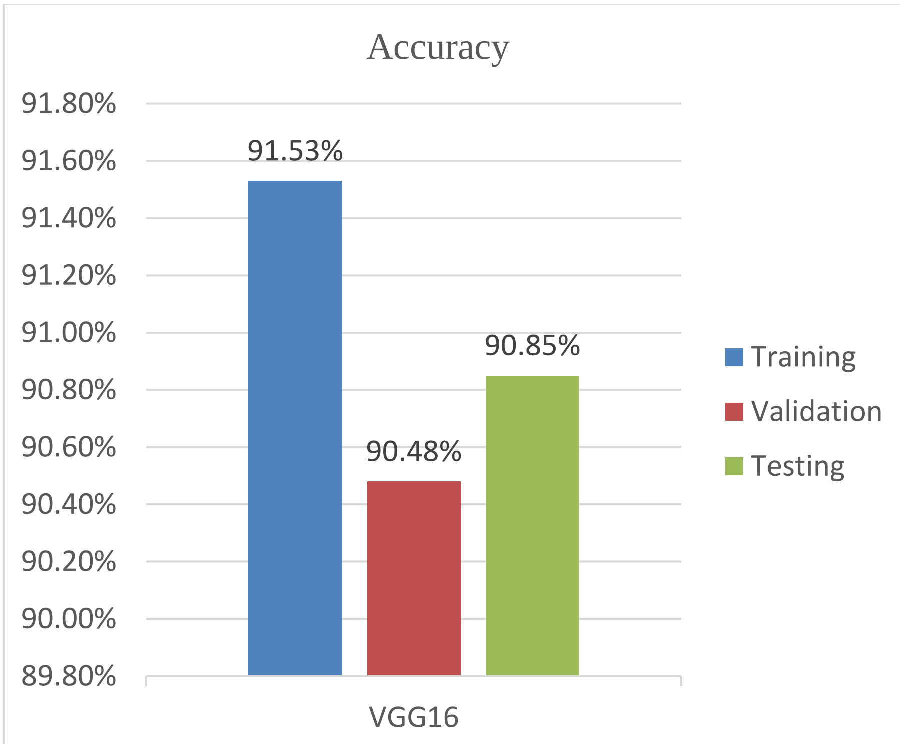

Fig. 4.7: Accuracy chart of VGG16.

The final layer of VGG16 has a total of 14,737,733 parameters. Before this, a max pooling layer, a flatten layer, and a dense layer were added. Before these three layers, we inserted the VGG16 model as a layer. In this model, there are 4,742,661 trainable parameters and 9,995,072 non-trainable parameters. In Fig. 4.8, the VGG16 model summary is shown.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 max_pooling2d (MaxPooling2D  (None, 3, 3, 512)        0
 )

 flatten (Flatten)           (None, 4608)              0

 dense (Dense)               (None, 5)                 23045

=================================================================
Total params: 14,737,733
Trainable params: 4,742,661
Non-trainable params: 9,995,072
_________________________________________________________________
```

Fig. 4.8: Model summary of improved VGG16.

4.2.3 MobileNetV2

For our research work, primarily we focused on using a pretrained model. The model that we were using MobileNetV2 [23]. We improved the MobileNetV2 model for gaining more accuracy. Overall, MobileNetV2's architecture includes a fully convolutional layer with 32 filters, followed by 19 residual bottleneck layers. To train the model we have to resize the images and the size of images is 224×224 pixels. Fig. 4.9, shows the plot graph of improved MobileNetV2.

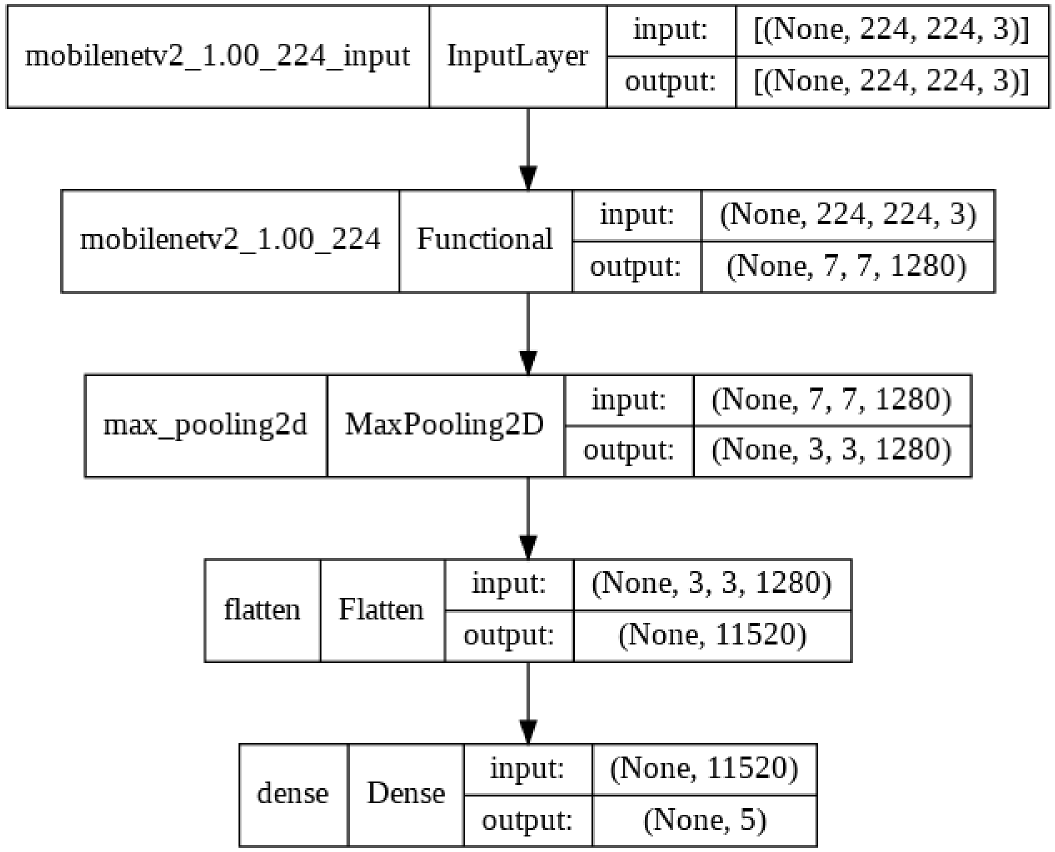

Fig. 4.9: Plot graph of MobileNetV2.

We achieved 95.74% training accuracy, 94.81% validation accuracy, and 95.43% test accuracy after 50 epochs using MobileNetV2. Table 4.1 shows the confusion matrix of the improved MobileNetV2.

Table 4.1: Confusion matrix of proposed MobileNetV2.

SL	Class Name	TP	TN	FP	FN
1	Healthy	65	85	2	1
2	Lumpy skin disease	28	122	1	2
3	Foot and Mouth disease	22	129	2	0
4	Brucellosis disease	11	138	1	3
5	Mastitis disease	20	131	1	1

MobileNetV2 has also performed well in classifying photos of all classes. Table 4.2 shows the improved MobileNetV2's class-by-class classification performance.

Table 4.2: Class-wise classification performance of MobileNetV2.

SL	Class Name	Sensitivity (%)	Specificity (%)	Accuracy (%)	Precision (%)
1	Healthy	98.4	97.70	98.04	97.01
2	Lumpy skin disease	93.33	99.19	98.04	96.55
3	Foot and Mouth disease	100.0	98.47	98.69	91.67
4	Brucellosis disease	78.57	99.28	97.39	91.67
5	Mastitis disease	95.24	99.24	98.69	9524

We can easily understand the accuracy of MobileNetV2 by showing the chart. In Fig. 4.10, shows the accuracy chart of MobileNetV2.

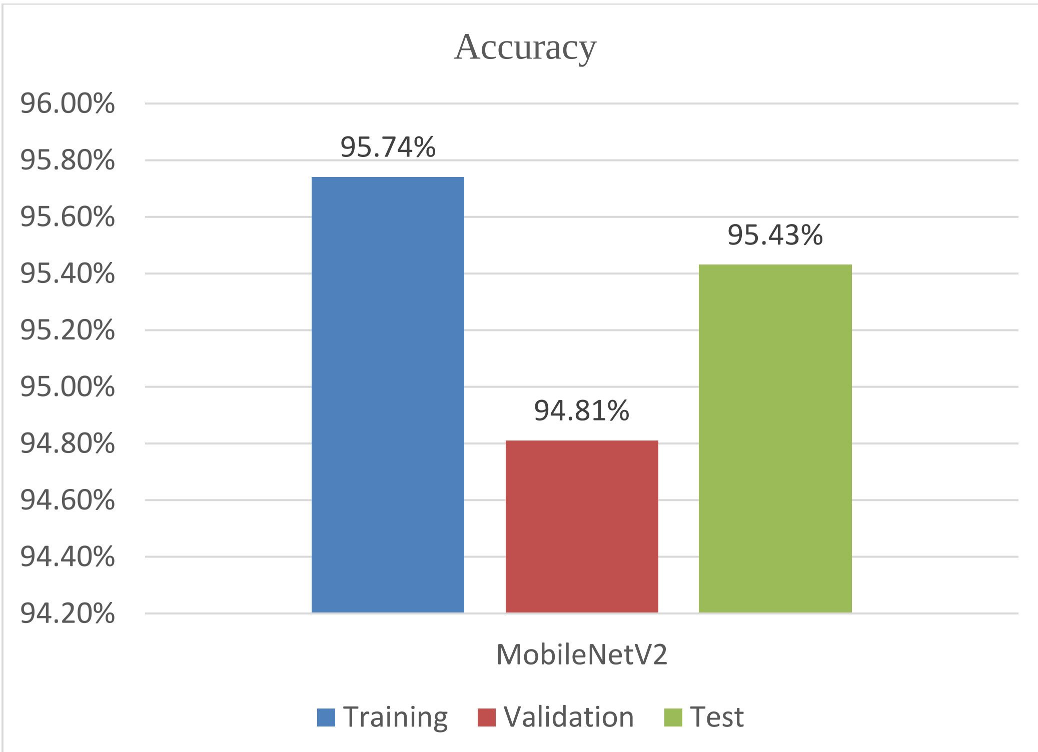

Fig. 4.10: Accuracy chart of MobileNetV2.

There are a total of 2,315,589 parameters in the enhanced MobileNetV2's final layer. One global average pooling layer, flatten layer, and the dense layer were added before this. We added the MobileNetV2 model as a layer before these three layers. There are 2,225,989 trainable parameters and 89,600 non-trainable parameters in this model. Model summary of improved MobileNetV2 is shown below in Fig. 4.11.

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 mobilenetv2_1.00_224 (Funct  (None, 7, 7, 1280)       2257984
 ional)

 max_pooling2d_6 (MaxPooling  (None, 3, 3, 1280)       0
 2D)

 flatten_4 (Flatten)         (None, 11520)             0

 dense_7 (Dense)             (None, 5)                 57605

=================================================================
Total params: 2,315,589
Trainable params: 2,225,989
Non-trainable params: 89,600
_________________________________________________________________
```

Fig 4.11: Model summary of improved MobileNetV2.

In Figure. 4.12 and 4.13, the accuracy and loss of both training and validation of improved MobileNetV2 are presented.

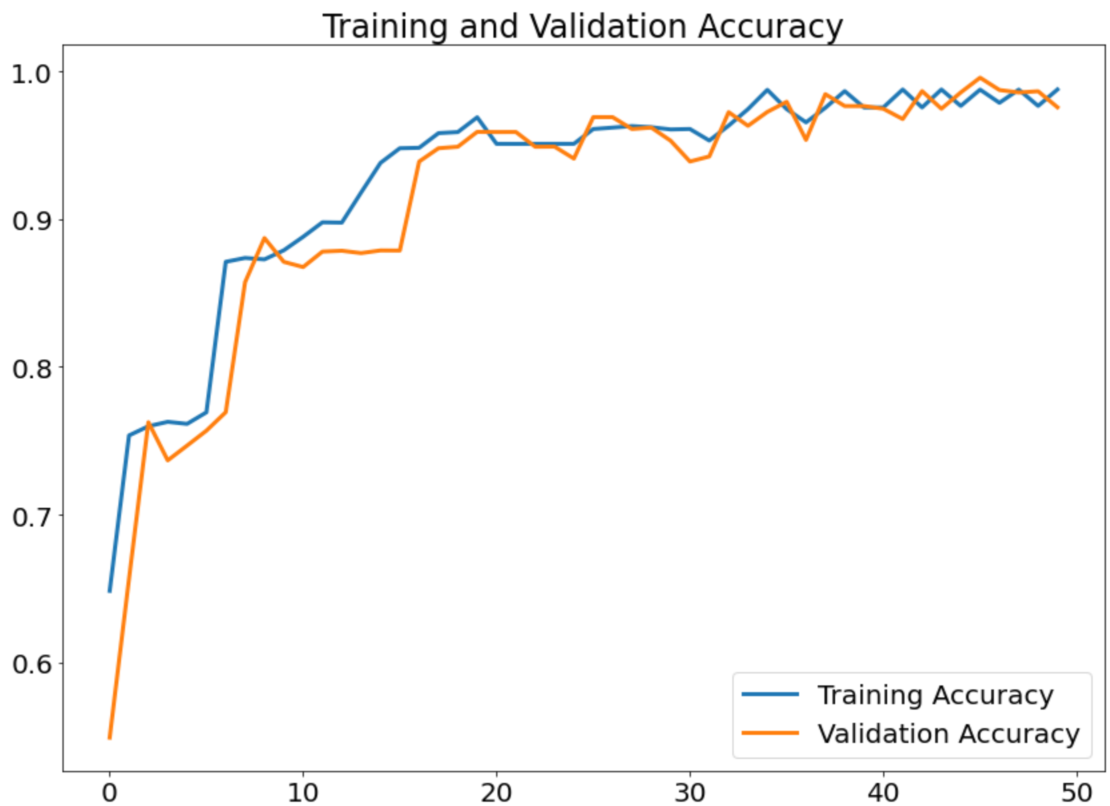

Fig. 4.12: Training accuracy vs. validation accuracy of improved MobileNetV2.

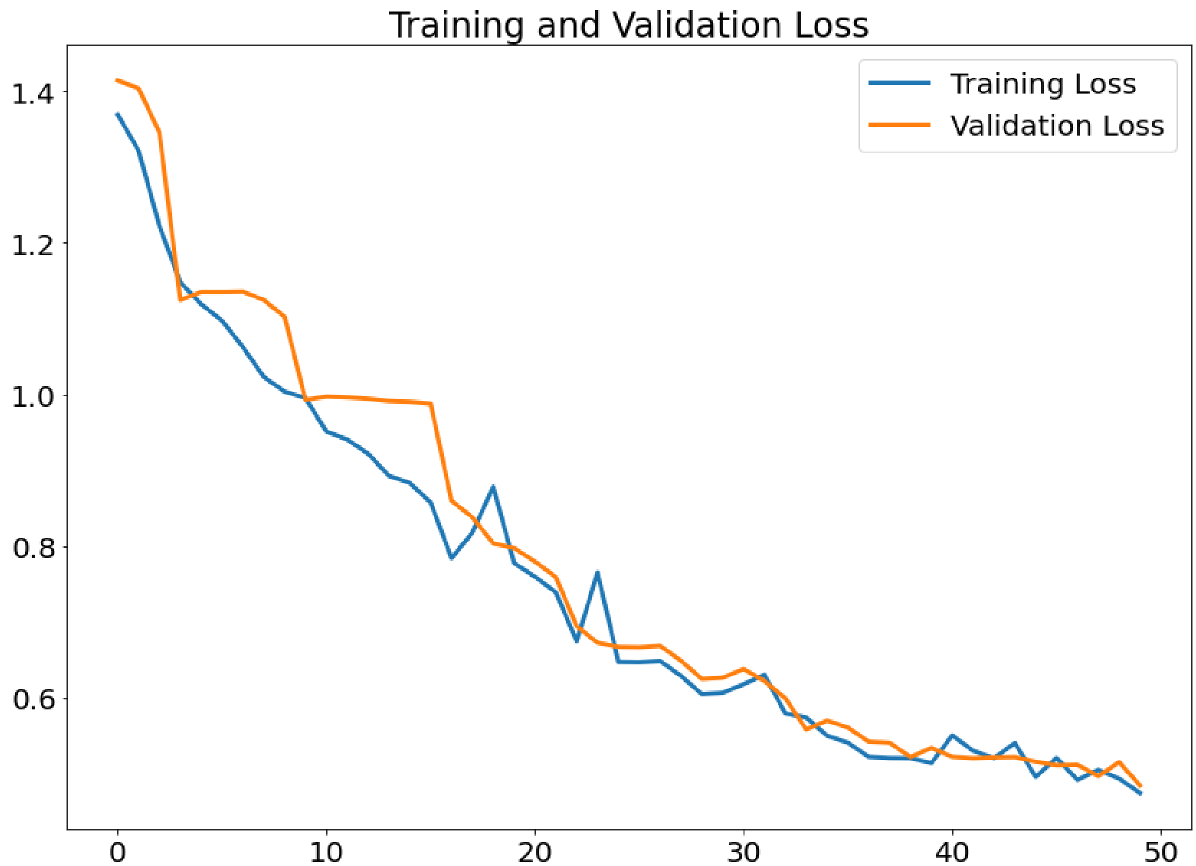

Fig. 4.13: Training loss vs. validation loss of Improved MobileNetV2.

4.3 Model comparison

In the used models, MobileNetV2 gives us the highest accuracy rate. It gives us 95.74% training accuracy, 94.81% validation accuracy, and 95.43% test accuracy. On the other hand, VGG16 has also gained a good accuracy rate. It gives us 91.53% training accuracy, 90.48% validation accuracy, and 90.85% test accuracy. Finally, we have AlexNet in third place by accuracy rate. It gives us 87.24% training accuracy, 86.80% validation accuracy, and 86.27% test accuracy. In Fig. 4.14, shown the comparison chart of three models.

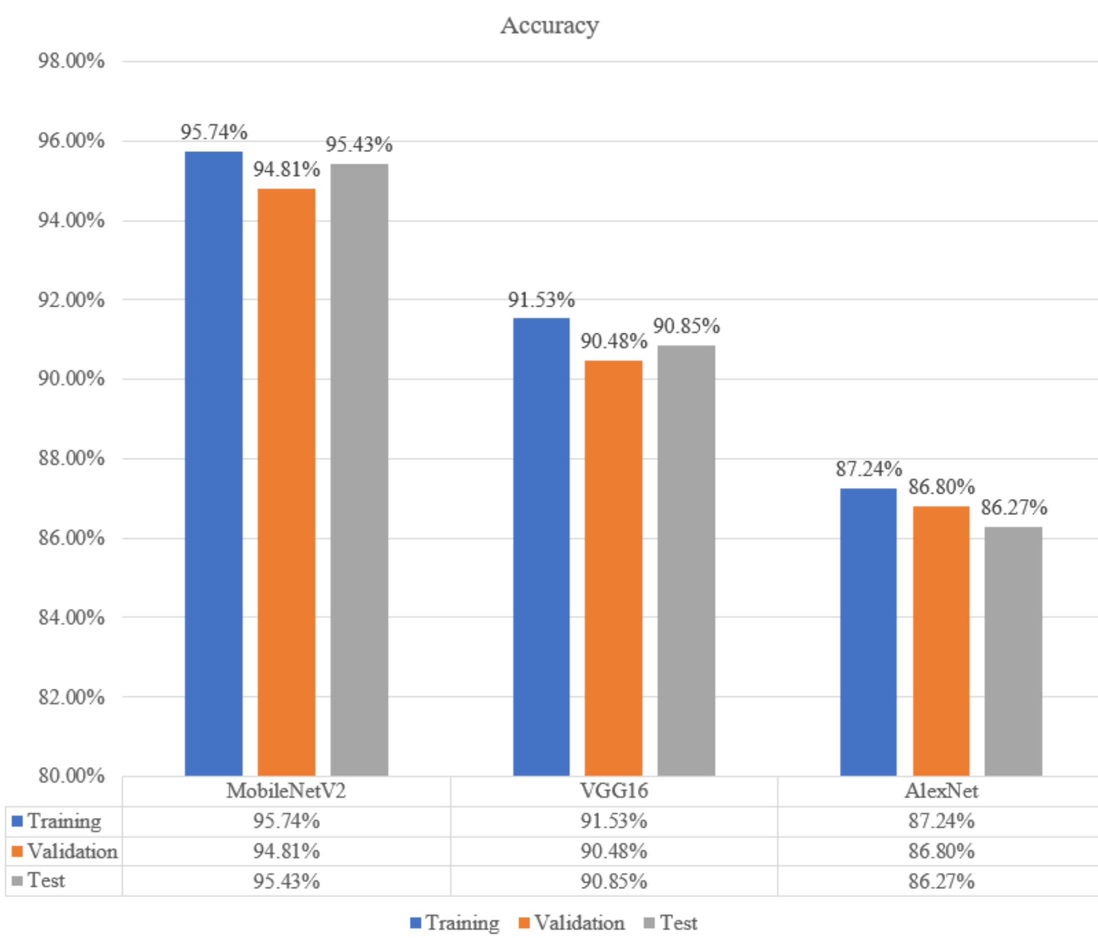

Fig. 4.14: Comparison chart of three model.

CHAPTER 5

Impact on Society, Environment, and Sustainability

5.1 Impact on Society

One of the major goals of this study is to improve the financial situation of cattle farmers. Bangladeshi farmers, like those in other South Asian nations, are inexperienced with contemporary agricultural methods. As a result, they frequently suffer financial losses. Cattle are susceptible to a variety of illnesses at any moment, making cattle farming a difficult endeavor. Farmers have to rely on their luck to make a profit. Cattle illness makes farming difficult. Our findings will aid farmers in detecting cow ailments early on. They will then be able to take steps to limit sickness and secure profit. Our technique will assist farmers in gaining a financial advantage in this way. This illness detection technology will also assist in other animal diseases. We were able to attain good accuracy by training the CNN models with a larger picture dataset. CNN is compatible with contemporary technology and maybe simply implemented on any platform. Our research will aid farmers and ordinary people who do not have a sufficient understanding of cattle illnesses. As a result, this study has a large social impact.

5.2 Impact on Environment

The cow is our important asset in livestock. So, cow disease is a thread. Cow disease can cause environmental issues as well. From our diseases study on cows, we found that some of the diseases are contagious and some diseases can spread to humans also. Though it has a limited possibility of spreading to people, it is not completely safe. Some diseases can take life also. So, the cowboy and people associated with cows have to be protected. One more thing is our country people are not so concerned about the dead cow. They often leave the dead cow here and there. As a result, they got rotten and spread smells and germs all around. This is a serious environmental threat. To solve this problem, we come out with our research, which will help the farmer of the dairy farm to recognize the diseases quickly and take initiatives as early as possible. Our proposed CNN models are capable of appropriately recognize cow diseases. These CNN models can be used in any smart software application. People would be able to detect diseases at an early stage using smart software based on this concept. This will help less down the death rate of cows, less amount spreading diseases as well as ensure a good profit. As the death rate declines, the likelihood of pollution decreases as well. As a result, our research will have a significant impact on environmental safety.

5.3 Sustainability Plan

Our research's goal is to help farmers in the early detection of cattle diseases. This model can be used by the Ministry of Agriculture and other agricultural organizations to help them work more quickly. Farmers will benefit financially from our research, and it will also have an impact on the national economy, as cattle demand is rapidly increasing in both domestic and international markets.

CHAPTER 6

Summary, Conclusion, Recommendation, And Implication for Future Research

6.1 Summary of the Study

In this work, deep learning was used to detect cattle diseases. The disease investigation, image collecting, technique implementation, and experimental evaluation are all included in this project. Throughout the year, we gathered images from various locations and created an image dataset for our study. We resized all of the images and improved the quality of the images using Jupyter Notebook. We opted to employ CNN in our study after evaluating a variety of similar research papers. One of the key advantages of CNN is that it is compatible with new technology. We use Google Colab to train our CNN models.

6.2 Limitations and Conclusions

In this research, we were using a total of three pretrained models for detecting cattle diseases. The models are MobileNetV2, VGG16, and AlexNet. The models are capable of properly recognize cattle disease, it is not without flaws. But among these pre-trained models MobileNetV2 performs better and accurate result that the other models. Other models also detect data but the accuracy is low in their case. In our case, MobileNetV2 performs well with our dataset. So, we give more importance working with that model to make a good outcome from our research work, there is one more thing to be mentioned that, we only detected four prevalent illnesses after visiting several locations. In our exploration, we only looked at four different cattle diseases. None of these model will not be able to detect other diseases if it is without four diseases. We suggested a new method for recognize cow disease using CNN in this study. CNN is a well-known source of information in a variety of sectors. The performance of our CNN models has been assessed, and it has been shown to be excellent. With clear photos, these CNN models operate quite well. This model also demonstrates its effectiveness in distinguishing between each class. We put a lot of effort into improving our dataset and making it more research-worthy. Farmers that raise cattle will benefit from the findings of our study. By assuring the quality of the cows, it would improve their financial situation. Cow demand is skyrocketing both in the domestic and international markets. This study has significant societal and environmental implications. The Ministry of Agriculture and other organizations can use the findings of this study to improve farmers' economic conditions and assure high-quality cattle output.

6.3 Implication for Further Study

AI-based solutions make our daily life easier than they were previously. Like electricity, AI changes everything. We'd want to integrate our CNN models into an Android app. Smartphone and internet users are growing at an exponential rate. Ordinary folks and farmers will benefit greatly from a user-friendly mobile application with appealing GUIs. Our CNN models can now distinguish four different illnesses from images. We shall see an improvement to recognize diseases in the future. In future research, a more robust dataset will be built. In the future, we'll concentrate on improving the precision of our CNN model. We hope to release a model for various animal illnesses that have already been pre-trained. The concept may be expanded and moved ahead with the help of the Ministry of Agriculture.

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APPENDICES

Abbreviation

KNN = K-nearest neighbors

SVM = Support vector machines

BPN = Backpropagation neural network

CPN = Counter propagation neural network

LBP = Local binary pattern

SGD = Stochastic gradient descent

GUI= Graphical user interface

ReLU = Rectified Linear Unit

Appendix: Research Reflections

I knew very little about machine learning, deep learning, or recognition algorithms before I started. My supervisor is a wonderful person who is always willing to help. He was quite helpful and provided important advice from the starting. We learned a lot of things during the process of research, including how to create a better dataset, how to develop CNN models, and how to avoid overfitting. Finally, I learned about several machine learning and deep learning Algorithms as a result of my study, and it has encouraged me to do more in the future.

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