CattleSavior: Towards implementing an Advanced External Disease Detection System through Deep Learning

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

Lumpy Skin Disease (LSD), Mastitis, Foot and mouth (FMD), Infectious Bovine Keratoconjunctivitis (IBK) are the most common external diseases of cattle which has become a concern for the farmers around the world. In fact, these diseases have already created a situation of panic mostly among the cattle farmers of the developing countries of Asia and Africa as cattles are dying and causing major economic loss every year. In most cases, these diseases cause permanent damage to the skin and leave scars as well as other health issues. Hence, it is very important to detect the affected cattle in time and thus provide adequate treatment as soon as possible. But, even in this age of science and technology, farmers generally detect these skin diseases with the naked eye which involves human error and late detection. In addition, a large number of farmers living in the rural areas are still relying on the traditional methods of treating disease-affected cattles. Therefore, accurate and early detection along with necessary treatment and cautions are crucial to minimize the adverse effects these diseases have on the farmers. In this study, we will build a modern detection system of several common external diseases of cattle by using image processing and deep learning. Furthermore, one user-friendly smartphone application will also be developed so that it becomes easier for the farmers to detect the diseases by the photos of affected area followed by some general suggestions for the treatment.

Keywords: External Diseases; Lumpy Skin Disease (LSD); Foot and mouth(FMD); Infectious Bovine Keratoconjunctivitis (IBK); Developing Countries; Deep Learning; Smartphone Application

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Chapter 1

Introduction

1.1 Introduction

The importance of livestock cannot be denied even in this modern world of science and technology. At present, not only the rural and underprivileged people but also the young and accomplished individuals are getting attracted towards livestocks farming. Generally, livestock is the primary source of protein, leather, fiber, wool and in most of the countries of Asia and Africa, it is one of the most common sources of direct and indirect employment. Besides, it is an integral part of the economy mainly in developing countries like Bangladesh. According to the Department of Livestock Service (DLS) of Bangladesh, in the fiscal year of 2021-22, livestock has contributed 1.90% of the country's GDP and the growth rate of GDP has become 3.10% with a 16.52% of share in Agricultural GDP. Furthermore, livestock provides 20% of direct and 50% of part-time employment [34]. In the rural village area of Bangladesh, a household without any livestock farm is hardly seen. In the Asian subcontinent, among the different types of livestock; cattle, sheep, goats, buffaloes, chickens, and ducks are the most common. Indeed, cattle is the major type of livestock that provides meat, milk, leather, organic manure, and many necessary things for everyday life. According to the livestock department, in the fiscal year 2021-22, the number of cattle in the country was 24.7 million, buffalo was 1.5 million, goats was 26.7 million and sheep was 3.7 million. And in the last three years, about half a million cattle have increased in the country[32]. Therefore, maintaining the health of the livestock is crucial for the overall development of the country. Different types of diseases are the prime threat to the well-being of cattle. Nowadays, external diseases are becoming more common and causing anxiety among the farmers as a large number of cattle are getting affected every year. Lumpy Skin Disease (LSD), Foot and mouth disease (FMD), IBK, Mastitis, Black quarter, dermatophytosis, dermatophilosis are the most common external diseases that frequently occur in this region. These external diseases can also become life threatening if not detected correctly and treated at an early stage. In addition, it also imposes long-term economic loss on the farmer as it degrades the leather quality along with milk production and various health issues. Nevertheless, most of the farmers generally detect these external diseases on their own and for treatment, they depend on the traditional methods of healing. As a result, due to human error and ignorance, in most cases, farmers suffer a significant amount of economic loss and in the worst case, their cattle dies. Therefore, early and correct detection of these diseases is very important in addition to accurate feedback regarding necessary treatment and cautions. In order to solve this problem, smartphones can be used as more and more farmers are becoming smartphone users day by day. In a prediction, The Global System for Mobile Communications Association (GSMA) has reported that more than 80% of mobile phone users will be using smartphones in the Asia pacific region by the year 2025. It also includes, India will have 85%, Pakistan and Bangladesh will respectively have 74% and 62% smartphone users [21]. Hence, in this technology driven world, a farmer can make the best out of his handheld smartphone to accurately detect the external diseases and get adequate suggestions for the treatment. In this study, a modern detection system of several common external diseases of cattle will be implemented by using image processing and machine learning. Moreover, one easy to use smartphone application will also be developed which farmers will be able to operate in their native language. By the help of this application, farmers can scan the skin of a suspicious cattle with the camera and get accurate results followed by some necessary suggestions for treatment and cautions.

1.2 Research Problem

Livestocks are kept specifically on a farm for financial gain. These are typically cattle, buffalo, goats, and sheep in Bangladesh. Since livestock also provides the majority of people with manure, meat, milk,labor and leather, it plays a significant role in a nation's wealth and economy as well. Additionally, resources from livestock are crucial for the support of landless people. Moreover, around one fifth of Bangladesh's population makes a living by working in the livestock and poultry industries. Besides, a sizable amount of the GDP is made up by the utilization of animal power for transportation, manure and fuel made from cow dung, and draught power for tilling the soil. It also plays a significant role in various types of agricultural production. In Bangladesh, there are now believed to be 25.7 million cattle, 0.83 million buffaloes, 14.8 million goats, and 1.9 million sheep, and 83.9% of all households possess livestock which is either animals, poultry, or both, according to the annual report of the Department of livestock services[34]. Moreover, the livestock population density of our country is significantly higher than the average of most other countries. However, despite having a large population of cattles and other livestocks, the country has a severe shortage of livestock products including milk, meat, and eggs. Nevertheless, one of the main reasons behind the shortage is lack of proper investments & research on quality production and maintenance of livestock. In addition, the lack of facilities training the farmers and taking necessary steps when needed in terms of better production and growth of the livestock is also responsible. For instance, this main source of milk and meat, cattles are facing frequent occurrences of some skin diseases such as Lumpy Skin Disease, Foot and Mouth Disease, Bovine Mastitis, Black Quarter, Dermatophilosis, Dermatophytosis and so on.

1.2.1 Lumpy Skin Disease

Lumpy skin disease is a viral infection of cattle and affected by LSDV(Lumpy Skin Disease Virus).This skin disease is usually identified by fever, enlarged lymph nodes, firm nodules and nodules are mostly seen in the hairless areas.Furthermore, this disease is transferred by by mosquitoes, flies etc from infected to uninfected skin and this disease can also be spread through impured feed, water, and equipment etc.Moreover, that skin nodules are approximately 5 to 50 mm in size and rise above the skin are the clinical symptoms of lumpy skin disease and gradually one or more nodules may form and eventually covered the entire body.This skin disease is like a pandemic in every side of our country's cattle farms and countryside households and getting worse day by day. This disease is bringing unbearable problems to our country like most milk production loss, infertility, abortion, trade limitation and sometimes death in our nation.According to a recent article of Dhaka Tribune, A unexpected outbreak of lumpy skin disease that is afflicting livestock in Shahjadpur upazila of Sirajganj district in Bangladesh is causing concern among cattle farmers ahead of Eid-ul-Azha. Within a week, the illness has already affected 200 cattle in the upazila. According to sources, the upazila has 7,000 cow farms and has been home to almost 3,000 000 cattle. For the upcoming Eid-ul-Azha, the cattle farmers of the upazila raised 100,000 cattle, which will be sent to several livestock markets, including Dhaka.

However, because lumpy skin disease has suddenly started to spread throughout the upazila, the cattle farmers there spend their days worrying that it will infect every part of the upazila.Despite injecting vaccines into the diseased animals, the Upazila Veterinary Office found no improvement in this area. Yeasin Mollah and Farhad Hossain, two cow farmers, said they are busy raising cattle to meet the demand for sacrificed animals during Eid-ul-Azha. Prior to Eid, they were getting ready to sell their cows in the neighborhood market. With the proceeds, they would pay all of their annual household costs. The farmers warned that if the skin condition spreads to the other livestock, they will suffer damages.From this condition , we can say that , lumpy skin disease is very contagious disease which can lead our country economy at very low stage and we will never be able to reduce the shortage of significant product of milk and meat as its about to be increased up to 6 to 9 percent per year in terms of milk and meat, the statistics said.

By early detection and taking proper precautions and necessary , this disease could be reduced and the rate of economy would be raised and shortage of products like milk and meat would be reduced.

Figure 1.1: Lumpy Skin Disease

1.2.2 Foot and Mouth Disease

FMD is very dangerous and infectious for cattle. It also has a notable economic impact. Compactly nurtured animals are more sensorial to this disease. Adult animals are affected less than youngs. FMD is seldom fatal in adults, but in young cattles it is often highly lethal for myocarditis or when the mother cow is infected by that particular disease. Almost 46-55% cattle are affected in Bangladesh by FMD. FMD determined by sores like blisters, fever on the lips, inside of the mouth, between hoofs . Maximum animals are recover who were affected by FMD, but it makes them weak. The "Aphthovirus" from Picornaviridae family causes FMD. There are 7 distinct serotypes responsible for FMD. The Asia-1, C, A, O serotypes are spreading and reported in cattle in Bangladesh. In Bangladesh about 70% of its population are engaged with livestock and agriculture directly or indirectly. FMD has a very bad impact on the dairy in Bangladesh, because of milk production loss and increasing of abortion rates. "The consequences of FMD in any species are reduced milk production, abortion, and mortality of 50-100% in calves and kits. "Total 850 affected households of Rangpur, Rajshahi, Dhaka, Khulna and Chattogram divisions of Bangladesh during July 2017 to June 2018 using a pre-tested interview schedule responding to the study objectives. In total, there were 4857 crossbred and 2138 native cattle in the affected household. The total financial loss due to the FMD outbreak was calculated as Taka 53172067 (Tk. 53.17 million or US$ 0.63 million) for 850 affected households. The percentage of loss incurred was the highest for the death of affected cattle (63.47%) followed by veterinary cost (10.71%), weight loss of fattening cattle (10.68%), reduction in milk yield (9.17%) and manpower loss for taking care of affected cattle (5.98%)" [34].

Figure 1.2: Foot and MOuth Disease

1.2.3 Infectious Bovine Keratoconjunctivitis

There is a cattle disease called Infectious Bovine Keratoconjunctivitis (IBK) or pinkeye, which has been causing big trouble for the people living in rural areas in Bangladesh. It's a bacterial infection that affects beef cattle, making their eyes all red and painful. The thing is, these cattle are super important for the livelihoods of farmers, so when they get sick, it's a real nightmare for the farmers and as a result this disease leads to reduced cattle productivity, and the economic losses and eventually those losses hit farmers very hard and unbearable.Additionally,another crucial problem which is seen that not everyone in these rural communities has easy access to veterinary care and many of them don't even know how to prevent the disease from spreading and eventually with all the cattle living close to each other, the risk of spreading the disease like very high and making it like its not going to be controlled easily. Furthermore,when farmers do try to get their cattle treated because of lack of veterinary and proper guidelines on how to defeat this disease eventually it costs them a lot of money, putting extra strain on their already tight budgets.Farmers are burdened with the costs of veterinary treatments and medications and those causes.To address this pressing issue, a coordinated effort is required like all the government agencies, agricultural experts should work together to implement disease surveillance programs and raising the awareness about preventive practices among the farmers and make veterinary services more accessible to rural areas. If those steps could apply perfectly then there is a chance that the disease IBK can be reduced and eventually the well-being of rural residents and the sustainability of the agricultural sector would be ensured in Bangladesh.

Figure 1.3: Infectious Bovine Keratoconjunctivitis

1.2.4 Bovine Mastitis

Bovine Mastitis, considered the most alarming disease that can be found among the cattles which may cause infection to the mammary gland and reduce milk production capability. This disease is caused by bacteria as a result of a certain injury of udder, or sometimes spread from human hands while milking it in unhygienic ways. Afterwards, the bacterias attack on the udder tissue of the mammary gland and finally make an attack on the defense mechanism system. Depending on the degree of sensitivity, this disease can be classified into three categories which are the clinical, sub-clinical, and chronic mastitis. Firstly, the clinical mastitis can be detected by noticing both the udder and milk quality. If any cattle is infected by this class of disease, her udder will be reddish and the produced milk will be less dense and full of clots and flakes[4]. Compared with clinical mastitis, subclinical mastitis has fewer visible signs. In this case, the milk production capability decreases like clinical mastitis, but the only difference is the increase of somatic cells[6]. This disease lasts almost for a month and the overall losses due to mastitis are immense. In recent times, it is recorded that, almost $147 is spent to properly diagnose a cow [16]. Also,the huge fall in the milk production caused 70% loss of the total losses [18]. Apart from that, a cow suffering from mastitis produces contaminated milk due to illness and there is a high chance of getting infected from other diseases. In extreme cases, udder may be permanently damaged if the disease is not detected or cured in time[6].

Figure 1.4: Bovine Mastitis Disease

1.2.5 Black Quarter

Black Quarter is one of the most dangerous bacterial diseases of cattle. Another name of Black Quarter is Quarter ill or Quarter evil. This disease occurs by clostridium chauvoei bacteria. For this disease, cattle feel pain at first then it would paralyze their leg. It creates a black spot on its leg. After that, it turned into their death. Moreover, it is also a very contagious disease. For example, if one cattle gets affected then whole dairy cattle may get affected quickly by it. A research team from Animal Science University, Chittagong, Bangladesh did a study on Black Quarter in 2006. They found that 0.4% of Bangladesh cattle get affected by this disease. Among them, 50.74% cattle died because of this prestigious disease. So, it is really important for our dairy farmers to detect this disease as soon as possible in the early phase.

Figure 1.5: Black quarter Disease

1.2.6 Dermatophilosis

Dermatophilosis is a bacteria-caused skin disease of cattles which is now spreading world-wide. Specially, in Bangladesh, around 13.51% of cattles are affected by dermatophilosis . In recent times, it is not limited to cattles, pigs, dogs, cats and even crocodiles are seen to be affected by it [7]. It is mostly seen among the newly born cattles, specifically the cattles having a weakened immune system. This disease basically spreads from Dermatophilus congolensis bacterias which are found in soil. In general, most of the cattles lay directly on the raw soil in farmhouses. There they get wet by rain or other natural factors which allows the bacterias to attack on their skin. In some cases, it also spread from insect bites which grew up in the wet atmosphere. This bacteria mostly affects the head and neck of the cattle. Because of this disease, the skin forms into scab or crust. Sores start to get visual in the infected areas, mostly in ears and legs and it may get all over the body through flies and cause 'lumpy wool' [2]. Animals who are extremely infected lose walking ability and lay to death at last.

Figure 1.6: Dermatophilosis

1.2.7 Dermatophytosis

Dermatophytosis, also known as ringworm or tinea of cattle, caused by dermatophytes fungi T.verrucosum [8]. It is the most frequently occurring disease and mostly seen in tropical countries. It has a low prevalence rate of 11%. It is classified into zoophilic (animals), geophilic (soil) and anthropophilic (humans) [5]. This fungus specifically attacks the skin, hair and nail keratinized tissue of the victim [9]. Therefore, it is an extremely contagious disease and can be easily transmitted through direct or indirect contact with infected cattles or sometimes this fungus can also spread from soil. The outbreak of the disease may vary depending on countries and natural factors like climate, humidity and temperature. In cattle, multiple circular lesions are seen in the chest and other spaces [14]. Hair loss is seen afterwards with multiple grey crust[5]. In recent times, this disease is quite hard to detect at first glance by which it gets almost late to cure the animal. Though curing and diagnosis of the cattle is not impossible but expensive as it requires chemical ingredients and antifungal drugs [3].

Figure 1.7: Dermatophytosis

1.3 Research Objective

Our research aim is to detect common external diseases of cattle and provide them with the correct solution immediately so that dairy farmers can decrease their economic loss.
1. Understanding the common breeds and external diseases in our country.
2. Understanding the economical loss and trouble for the diseases.
3. Analyzing the number of smartphone uses in dairy farmers.
4. Build a model which will detect the common external diseases properly.
5. Move the model in an application so that our dairy farmers can detect the common external diseases quickly as well as get the correct solution.
6. Reach out to the dairy farmers and we will suggest they use our application for their diseases detection and solution.
7. Analyzing the decrease of economic loss and less trouble after using our application.

Chapter 2

Literature Review

In this section of the literature review, we have read most of the previous works done in this field. The study of each paper has enriched us with various ideas and methods of implementing a model, ways of data collection, different challenges along with the major insights of several aspects of a subject. In the following, we have enlisted the summaries of different papers in the field of our study into two aspects as Human Computer Interaction (HCI) aspect and Machine Learning (ML) / Deep Learning (DL) aspect.

2.1 Related works in HCI aspect

Firstly about detecting some common Bovine diseases, A research conducted by Shivaanivarsha et al. [31] about detecting some common Bovine diseases using a deep learning CNN model, TensorFlow Lite, which was tested and trained using about 570 images. It also states that almost all livestock are situated in rural areas where the biggest challenge for dairy farmers is to get quick veterinary treatment. So, it is very important to detect skin disease very early. Moreover, skin disease increases very quickly. This paper mainly deals with four types of bovine disease detection and they are Bovine Mastitis, Lumpy Skin Disease, Papillomatosis, and Photosensitisation. In this paper, they have used a teachable machine that can transfer knowledge from one model to another and accurately classify diseases. Its accuracy is better than manual machine learning algorithms. It has 96% accuracy in Bovine Mastitis, 98.5% in Lumpy Skin Disease, 98.6% in Papillomatosis, and 99.9% accuracy in Photosensitisation. So its overall accuracy is 98.5%. Then they created an android app through their model and Tensorflow lite code android studio. Here farmers can detect disease in real time by webcam or photo. The app will show suggestions and nearby veterinary hospitals for cattle. But this app can only detect 4 diseases. In another paper, FERNANDO et al. [1] stated the way of detecting Mastitis using EC (electric conductivity). Here they measured foremilk and post-milking strippings from 92 cows with 368 quarters samples in the afternoon after a milking interval of approximately 10 h. The infection had been determined from strict foremilk by the bacteriological analysis. It is classified by pathogens based on the significance of the organism (isolated). On foremilk, the somatic cells were counted as samples by the membrane filter DNA method. As the EC increases with infection that's why the conductivity was higher in postmilk than the foremilk in the sample quarters who were infected with primary pathogens. There are three methods of using milk conductivity: Absolute conductivity, Differential conductivity, The combination of those two(which is most successful and accurate). It can classify 90% accurately. Accuracy of infections with absolute conductivity 62.8% (foremilk) and 96.2% (postmilking). In both normal and infected quarters in post-milking strippings the somatic cell count was the same but the elevated conductivity tended to be higher at the same time. Milk conductivity appears to hold a guarantee as a pointer of sub-clinical mastitis. Here, discriminant investigation was utilized to decide the capacity of conductivity and somatic cell count to separate between uninfected and infected quarters. For the vulnerability of secondary pathogens, only infections by primary pathogens were included within the "infected" group for discriminant examination. 76 of 368 quarters were infected. Staphylococcus aureus was isolated from 33 quarters, Streptococcus Uberis from 11, and coliforms from 9. Twenty-three infections by nonhemolytic micrococci and Corynebacterium boris were regarded as secondary infections. The lowest error rate for the conductivity of strippings showed that the degree of divergence between conductivities of strippings from normal and infected groups was greater than that for conductivities of foremilk or Log (somatic cells count) between the same groups. A number of misclassifications were greatest when the conductivity of foremilk was used. There was a common promise between infection status and somatic cell count, in that most normal quarters had low somatic cell count. The accuracy of detecting infections by secondary pathogens was relatively low (61.9%). Postmilking Conductivity was a more active indicator of infection than foremilk.

In addition, Katamba et al. [13] discuss livestock external diseases detection. They introduce a mobile application namely Jaguza Livestock App which makes cattle management easier. This app comes with a bunch of essential features like early disease detection, real-time animal tracking, animal disease diagnosis, veterinary doctor information, and weather updates. Also, it includes SMS and USSD systems, and GIS surveillance which help in analyzing and reporting livestock updates. This app can run through both offline and online. In online mode, it connects all the users from different districts in a centralized server. The offline system allows users in rural areas to use the app without the internet and provides access to see previously saved information. The diagnosis system is made based on the predictive and analytic modules which take symptoms as input and provide the estimated disease as output with all the details of that disease. The main aspiration is to boost livestock production, ease the management process, and early detection of general disease by continuous mobile monitoring methods.

2.2 Related works in Machine Learning (ML) and Deep learning(DL) aspect

Safavi et al. [27] elaborate on the idea of identifying the occurrence of LSDV infection based on geographical and climatic characteristics by using a machine learning algorithm, Artificial Neural Network (ANN). At first, the authors address the Lumpy skin disease virus (LSDV) and its negative impact on the cattle firm industry. Moreover, It is a highly contagious viral disease and it hampers the ability of cattle milk production as well as beef production. Besides, it can be transmitted very fast from the infected to the uninfected animal's body through water, food, and so on. Then, they reviewed many researchers' identification of various diseases using different machine learning algorithms depending on variables like humidity, temperature, wind speed, etc. For instance, a researcher in China has developed a neural network model for identifying the number of humans who are affected by diarrhea. Another research is about predicting the confirmed death case of COVID-19 in different countries. Afterward, the authors narrate their key objective which is to build a model which can predict lumpy skin disease by estimating the history of lumpy virus infection in different countries between 2011 and 2021. A data set that has five attributes named LSDV data, Meteorological data, Animal density data, Land cover data, and Elevation data is used. Different data pre-processing methods are applied to the dataset for fitting different models. In terms of selecting features, they use two models. The SelectFromModel class is used to choose features based on relevance weights. Then, they also use another method to choose parameters for each machine learning model. In the testing and training phases, they utilize a variety of machine learning techniques including logistic regression, support vector machines, decision trees, random forests, adaboost, and bagging artificial neural networks. Among the models, they achieve 97% accuracy by using climatic and geospatial features as predictive variables in the Artificial Neural Network (ANN) algorithm. This predicting algorithm can be very helpful in detecting the location early where the chances of the outbreak of LSDV infection are very high. Based on that, different awareness programs as well as preventive measures like vaccine campaigns can be run to minimize the adverse effects of LSDV.

In another work on Lumpy Skin Disease [22] a deep learning approach is used to detect the disease through semen that may infect cows and their embryos. At first, this paper talks about the importance of AI for detecting viruses and their families and its impact on cattle as well as the economy of a country. The Neethling strain is the main symptom of lumpy skin disease. Other signs include a few modest varieties of confined skin nodules. Then, the authors develop a machine learning-based architecture for detecting the disease. Afterwards, the simultaneous execution of two controlled trials is carried out for the experiment. Moreover, they conduct experiments on cattle by putting a virus on young heifers. The 27 days of the experiment are recorded. On the very first day, fresh semen laced with a field strain of LSDV is used to inseminate eleven young beef heifers that had never been exposed to this virus. Also on Day 1, six of the young heifers are superovulated using pregnant mare serum gonadotropin. The embryos from these heifers are flushed on Day 6. From Day 4 to Day 27, blood and serum samples are collected in order to detect the presence of LSDV by PCR, virus isolation as well as the presence of antibodies against LSDV. On Day 10, they identified LSDV followed by mild LSD in two of the heifers and severe generalized LSD in three additional heifers. Due to severe, unresponsive strangury, two heifers are inhumanely put to death. LSDV is basically found by electron microscopy or virus isolation mostly in embryos, organs, and blood of infected animals. On Day 27, eight heifers are seroconverted and afterward, there remain only two unaffected control animals. There has never been a report of experimental seminal transmission of LSDV in cattle. Eventually, after doing their experiment of 27 days and collecting a dataset, they apply different machine learning models that use numerous classifiers. Then, after feature extraction, they use different pre-trained models such as Inception-v3, VGG-16, VGG-19, etc., and classifiers named KNN, SVM, NB, ANN, and LR. Then, the authors further categorize the retrieved features using their manually compiled dataset to test the work. With this methodology, the cutting-edge solution achieves 92.5% accuracy over the test dataset.

Dofadar et al. [28] also explained 10 machine learning algorithms that can detect lumpy skin disease. This disease mostly occurred because of illness including fever, and infertility, and eventually it decreased milk production, creation, and so forth. If the farmer is able to predict the reason for this disease sooner, it can greatly reduce the economic loss because cattle infected with Lumpy Skin Disease do not tend to live long. In this research, the authors used a variety of machine learning models to predict if the cattle are afflicted with Lumpy Skin Disease or not. Ten machine learning classifiers are employed and for assessing the effectiveness of algorithms they use assessment metrics. Eventually among 10 models, they achieve 98% accuracy in RandomForestClassifier and LightGradient. In the first phase of this paper, the authors talk about the challenges of classifying skin disease because of imperfect output, high computing cost and so on. Then they discuss the advantages of using machine learning models and their success ratio of predicting disease. Further, they use various techniques to resolve data before applying them into the classifier. For data collection, they employ the classifiers from Mendeley data which is assembled from diverse sources. This dataset has 24803 occurrences, 19 unique characteristics and a class label. In the methodology segment, authors describe their used algorithms which include KNN, LogisticRegression, RandomForest, SVM, SGD, LGBM, GB, GaussianNaiveBayes, DecisionTree and XGB. They also mention the input sample of data should not be imbalanced. Among the 10 classifiers, LG(Light Gradient) and RF(RandomForest) have the highest accuracy. Moreover, they apply data in two classes; regular class and lumpy class. Over 87% data is used in the regular class and the rest of the data is a lumpy class. Afterward, they identify that the models perform better when the data is modified by the smote technique. In the conclusion of the future work segment, they talk about the advantages of those two models to forecast lumpy disease by using climatic and geospatial variables. Furthermore, they also talk about the challenges of their study which is the lack of appropriate data and predictor variables.

Furthermore, Suparyati et al. [32] apply some resampling techniques to detect Lumpy Skin Disease of cattle. It also states different aspects of lumpy diseases and how it is becoming more common in many regions of the world. Then, they also elaborate on the importance of detecting disease early so that the economic damages won't be higher by LSD. Then, the authors describe the data that is used in their study and where it has been collected from. The data is taken from Mendeley and using it forecast the presence of lumpy virus in a particular area. In the data set, they find many imbalances in the dataset and to fix it, they use a technique called smote. Then RF classifier (RandomForest) is used on the data to detect lumpy infection. The RandomForest model performs admirably on data that has been over and under-sampled. The evaluation of performance measures reveals that SMOTE outperforms Random Undersampling by 1% to 2%. Additionally, SMOTE is superior and has somewhat higher precision than Random Undersampling in terms of Recall rate. It is the measurement that they want to maximize in order to discover lumpy situations. Actually, in this study, the authors have given more focus on how to balance data instead of model optimization.

Motohashi et al. [19] proposed a new model to detect subclinical mastitis by using some indicators acquired from the auto milking system. Bovine mastitis is actually the inflammation or swelling of the udder of a cow. As milk production is directly related to it, this disease can create a huge economic loss for the dairy farmers. Among the two types of mastitis, subclinical mastitis does not show any visible symptoms. Thanks to the development of the auto milking system, it has become simpler to monitor different indicators of milk such as protein, fat, milk yield, lactose, electrical conductivity, flow rate of milk, and so on. In this paper, SVM or Random forest algorithms were used to train the model and to compare the performance. The risk values are calculated based on lactate dehydrogenase used to feed the model. Electrical conductivity in milk which is measured by the auto-milking system is used as the time series attribute of the model. For training the model, a total of 110 cows with 10699 samples among them 972 subclinical mastitis and 9727 fine samples were fed into the system. And for testing the model a total of 535 sample cows with 25033 samples tits were used. Depending on the maximum electrical conductivity and minimum electrical conductivity in milk, the model predicts mastitis when the prediction probability is greater than 0.5. Also, by analyzing the variation of LDH and HN mastitis risk the model can alert the farm staff when HN mastitis risk is greater than 70. In terms of sensitivity, this model is able to detect subclinical mastitis with an accuracy of 81%. Besides, it has a precision of 46%. In addition, in some cases, earlier detection of subclinical mastitis can be possible by measuring LDH values.

Puig et al. [30] explained a model using common behavioral variables such as eating behavior and physical activity and the detection is done by configuring these data with a Machine Learning Algorithm. Bovine Respiratory disease is caused due to both virus and bacterial attacks on cattle. These parasites first attack on the upper respiratory tract of the animal and slightly start to attack the lung and the defense mechanism system. The detection of this disease in cattle was based on finding similarities of clinical signs and monitoring the daily behavior of the animals. These behaviors are nothing but the way of waiting and physical activities. Information was gathered from those activities and used as variables then configured through Machine Learning Algorithm. Though both Conventional BRD Diagnostic Methods and automated registration methods were discussed, it was found that the automated registration system was much more efficient. This whole thing is actually an app-based approach where the farmers are notified the devices find any sign or any growing sign of the disease. The method is called an automated registration system where each animal will have an EID (Electronic Identification) and BAS (Behaviour Assessment System). Here, each EID device creates a unique number of data received from several physical tags (ear tags, pedometers, collars, and microchips).

Then this data goes through a continuous monitoring process which is basically the analysis with a Machine Learning Algorithm. As the whole system is dynamic, the more it gets data the more it learns and makes decisions on it. Therefore more BRD (Bovine respiratory disease) detection is possible. This data is transferred to the transceiver from the transponder through a radio frequency identification system (RFID). After that, the information is transferred by an RFID reader to the user. In this way the farmers will be able to detect Bovine Respiratory disease easily.

Vyas et al. [17] have shown a pathway to detect FMD (Foot and Mouth Disease) and Mastitis of cows with the help of a Machine Learning algorithm (Neural Network) and also some sensors which will give info about the physical condition of cows. FMD is a virus-caused disease which leads a cow to fever and blisters. On the other hand, Mastitis is a bacteria-caused disease that specifically affects the mammary gland and the udder of a cow. Both of these diseases reduce the milk production capability of a cow and have an almost similar detection process. To detect these diseases several sensors(temperature, rumination, motion sensor) and a microcontroller (Raspberry-pi) were used. The approach was simple. First of all, all the sensors were placed on a cow in different portions of their body and all the sensors were centrally connected to Raspberry-pi to one similar network. All the data from sensors circulated through Cloud to Raspberry-pi. For detection and unique identification, RFID tags were used and standard values of all the variables (Temperature, Rumination and Motion) were stored and compared with received data with the help of Artificial Neural Data classifiers.

Rony et al. [23] have proposed a model by using CNN with pre-trained models such as AlexNet, GoogleNet, and ResNet. This is the first work for Foot and Mouth Disease by using CNN architecture. For this research, they collected a total of 300 raw Healthy and Foot and Mouth Disease affected cattle. Then they convert them into a total 1038 number of augmented images. For their dataset, they resized all their images for AlexNet, GoogleNet and ResNet according to their need. They mainly use transfer learning for their CNN to reduce training limit time and generate lower regulation errors. There are four types of transfer learning which are AlexNet, GoogleNet, ResNet, VGG. Firstly, AlexNet is a CNN architecture that performs on GPU. Secondly, GoogleNet is a CNN that is without pooling layers. The input size is $224 \times 224 \times 3$ and the output size is $1 \times 1 \times 1000$. Finally, ResNet has 152 layers. ResNet is mainly used for ILSVRC-15. They get the highest accuracy at 95% in GoogleNet where precision is 94%. This model will help the farmer to detect FMD quickly.

In terms of some dermatological skin diseases, Kumar et al. [10] elaborated the way of detecting Dermatological diseases (Human) using dual stage approaches: Computer Vision and Machine Learning. Now, it gives up to 95% accuracy . Here the architecture and methodology is divided into two steps: step 1 - ComputerVision: It has two parts, Process the picture before use in analysis which is taken by smartphone, and extract the essential features color-codes, infliction size, etc. Secondly, using the extracted features to detect that disease with ML algorithms. In step 2, Machine Learning is used to refine the classifications of images and gives good detection. The system takes all these inputs from a user who has access to various histopathological attributes and detects the disease. The system used Neural Networks, KNN Model, Decision Trees. Then, the data sources are some colleges and universities where in Stage-1, Image Processing is used to enhance the accuracy of extraction the feature from the color images are processed using eight different preprocessing algorithms such as Binary image, Grayscale image, RGB extraction, Sobel operator, Sharpening filter, Smoothing filter , Median filter, YCbCr. In Stage-2, it follows Conversion of RGB color space into HSV color space and then identifies the shape. Then, the skin affliction components are extracted using Euler's value. After that, a threshold limit was used for indication of inflictions. Then it extracted the presence or absence of nail patches. Then it extracted the presence or absence of pustules in the skin. Stage-3 is Identification. In Stage-4, the Machine learning model used kth Nearest Neighbor (kNN), Decision Trees (DT), Maximum Entropy Model, and Artificial Neural Network for prediction. Here, it gives 95% accuracy combinedly.

Ajith et al. [11] talked about the detection of human skin diseases using smartphones. It takes an image as an input prototype from the patient, and then using the Image Processing method it gives output. The training part performs the image processing method based on the database and it analyzes the image. The training part generates the features. Whereas, the testing part which contains an image goes under processing and generates the features. Then all these features are compared and classified. Here it works on six diseases and they created six different databases for each disease. After that, for implementation, the Discrete Cosine Transform(DCT) transforms that image (spatial domain to frequency domain). Here it also separates the image into spectral subbands depending on the importance. Further, in Discrete Wavelet Transform (DWT), wavelets progressively break down functions within the frequency domain and hold the spatial domain. It assumes images as 2D signals. DWT gives frequency components, indicating the occurrence time. 2D signals have 4 subbands. The LL represents the approximated form of the initial image. HL represents the horizontal corners of the initial image. Then, LH represents the vertical corners of the initial image. HH represents the diagonal edges of the initial image. Here, the diseases were first identified using DCT with coefficients(8, 16, 32,64). For DCT the highest accuracy gives 16 coefficients, for DWT the highest accuracy gives level 1. After the combination of all three it gives the highest accuracy up to 80%. In addition, some papers were reviewed where different types of diseases were detected using different methods.

ALEnezi et al. [15] showed a method that can detect four different human skin diseases through Machine Learning and Image Processing with a 100% accuracy rate. In the general case, the detection of skin disease can be both costly and time-consuming as it uses laser and photonics-based medical technologies. But this process needs only a simple camera and working computer which will give a faster and accurate output. The method is divided into four parts (taking input, preprocessing, feature extraction, and classification). Firstly, it will take a digital image as input then it is preprocessed by resizing the shape which reduces the processing time. In the feature extraction section, the AlexNet CNN model is used where different individual layers are used for visual recognition and processing the natural language. The last step is the computer vision method. It basically classifies the disease according to symptoms through a Support Vector Machine (SVM). Moreover, the human skin cancer detection model is also reviewed.

Ansari et al. [12] talked about skin cancer detection using Image Processing and (SVM) or Support Vector Machine algorithms. Here the image (dermoscopic) of the skin, then goes under some noise removal, and image enhancement pre-processings. Now to classify the pre-processed images, those have to go under some thresholding method to extract some features of that image using (GLCM) or Gray Level Co-occurrence Matrix methodology. After extracting all the features, SVM is used to detect whether the given image is affected by cancer or not. Now, Skin cancer mainly begins at the outmost layer out of the three layers of skin, and they are made of squamous cells or the outermost layer, basal cells or the middle layer, melanocyte cells or the innermost layer. The first two are non-melanoma skin cancers and they respond to the treatment but Melanoma is very dangerous, it quickly spreads in the body. Here, the Biopsy method of detection is very time-consuming and painful and there is also a chance to spread the cancer into other parts of the body that SVM methodology proposed. Now the total implementation is done where it takes dermoscopic images as input, it works like a magnifier that is used to take pictures of body parts. Then, in pre-processing it removes unwanted distortions or noise and enhances important features. Three major things need to be done before pre-processing the images which are grayscale conversion, removing noise, and finally enhancement of images. In grayscale conversion, the image just reserves the brightness parameter of pixels. Each pixel value carries the value of light intensity. Here, colored (RGB) images are converted into grayscale images by using the weighted sum method. In Noise removal, it removes unwanted noises, but it is difficult to decide the features that are real or caused by noise. Noise is basically the unintentional variations of pixel values. It uses a median filter which is implemented by a window which can slide freely. It has an odd length to remove noise and it is nonlinear and leaves edges invariant. Every sample is sorted by its magnitude and the centermost value is the median of the sample(within the window) and that's the output. In Image enhancement, it increases the visibility of important features, using contrast enhancement. After that, segmentation is the process of removing those pixels which contain similar attributes. from a given image. Here using maximum entropy thresholding. At first, it takes the gray level of the actual image and then it calculates the histogram of grayscale, then separates the foreground from the background using maximum entropy. After that, it obtained a binary image which is black and white. And finally, this method has a success rate of 95%.

Another different method of cattle disease detection is discussed in a paper by Taneja et al. where early lameness is detected in dairy cattle and fog computing is used which is a data-driven approach of machine learning (Taneja et al. [20]). This paper discussed why timely lameness detection is very difficult to identify in cattle. Only human observation is not enough as the detection can be late due to possible human error. Therefore, in order to identify the lame cattle accurately in the early stage of the disease, they have developed an application where machine learning along with some data analytics techniques have been used. To monitor the activity of each cow, long-range pedometers are used which provide accelerometric data from these sensors. Then, a time series of regular behavioral activities is formed by aggregating all the data at the fog node. Furthermore, this information of the fog node is sent to the cloud for analysis. This hybrid model of classifying and clustering identifies each cow as either Lame or Non Lame which has the sub categories: Normal, Mildly Lame, Lame, Severely Lame. After detection, an immediate notification is directly sent to the farmer and provides him the information of his cattle. This system can detect a lameness-affected cattle about 3 days ahead of the farmer with an overall accuracy of 87%. Moreover, in this model, an 84% reduction in data transmission to the cloud is achieved thanks to the fog computing algorithm. Therefore, this study has successfully paved the way to isolate the cattle so that immediate treatment can be provided to the cattle to avoid any kind of further effects of it.

Volkmann et al. [25] also used acoustic analyses and machine learning to detect claw lesions in dairy cows. They have shown that lameness can be automatically detected by the detection of claw lesions using the sound impact of the cow's feet and floor in a farm. If animals are affected by any disease of the claws or limbs, an altered gait pattern is shown. By the analysis of a cow's gait using machine learning, this serious problem of claw lesions which is causing a significant amount of economic loss for the farmer can be detected and thus also identify the lameness. A panel consisting of 2 layers was installed on the slatted floor to analyze the sound when a cow walks on it. By measuring and analyzing a total of 640 sound files from 64 cows, a model was built to predict and classify lameness with the status of the cow using a machine learning approach along with a random forest algorithm. For the influencing factor,38 different attributes of the measured sound files have been used. The gold standard for comparing a healthy cow with an affected one was a 2-point hoof-trimming. This gold standard is compared with the output measured sound and by analyzing the difference it can identify the affected cow with claw lesions. This model has a sensitivity of 81% with 97% of specificity. Finally, the 80% of Cohen's Kappa value indicates an overall good adjustment between different parameters of the model.

In the paper of Workee et al. [26], machine learning is used to identify four different skin diseases. [25] It covers the detection of lumpy skin disease, dermatophytosis, dermatophytosis, and wart diseases which are very threatening for the farmers as they can cause severe damage to the skin of the cattle and even death. Besides, if these diseases are not treated at an early stage, it can impose a huge economic loss for the farmer. A cattle skin disease identification model is developed by using three different image filtering techniques such as median filter, Gaussian filter, and Gabor filter. Then, the model compares these three techniques and after that, CNN and HOG are used for hybrid feature extraction. Afterwards, in order to classify them SVM is used. As CNN doesn't stay constant for rotating, illumination changing or other types of image manipulation and transformation, the HOG technique is used. In this study, they used a total of 765 images for the four different skin diseases. As CNN requires a huge dataset, a total number of 2000 augmented images are used, and from that 80 percent of the data consisting of 1600 images is assigned for training the model and 20 percent of the data which includes 400 images is allocated for the testing of the model. In CNN, this model has an accuracy of 96.5% where HOG achieved 93% of accuracy and it increased to 98.75% using hybrid features.

Rony et al. [24] has proposed an idea to detect cattle external disease by using CNN, VGG-16, and Inception-V3 . They only work on the three most common cattle skin diseases all over the world which are Foot and Mouth Disease, Lumpy Skin Disease, and Infectious Bovine Keratoconjunctivitis. They found that 55.13 million cattle are affected by Foot and Mouth Disease in Bangladesh. They also found that 9993 cattle were affected by Lumpy Skin Disease in Chittagong, Bangladesh. These diseases are not only common in Bangladesh but also common all over the world. To solve the problem, they bring a deep learning technique which is based on VGG-16 and Inception-V3 architecture. VGC-16 is a pre-trained model which has sixteen convolution layers. On the other hand, they used Inception-V3 for object recognition and assisting in data exploration. They primarily used 600 raw images for their training and test where they used 200 images for Lumpy Skin Disease, 250 images for Foot and Mouth Disease, and 150 images for Bovine Keratoconjunctivitis. They used a total of 480 and 120 raw images for training and testing their model. They also used data augmentation and that's why they got a total of 6000 raw and augmented images. After that, they got 92% accuracy in CNN, 95% accuracy in Inception-v3, and 91% accuracy in VGG-16. So, they got the highest accuracy by using Inception-v3. In Inception-v3, they also got 93% sensitivity and 96% specificity. Here, transfer learning also helped to increase the accuracy. But the limitations they faced were that accuracy decreased after some iteration and it couldn't classify disease properly because of less dataset.

After studying all these papers, we have found that there have been numerous models implemented using different models and techniques as well as scope for future work. Hence, reviewing these papers has given us an overall idea of how we have to approach the detection methods for different diseases. In most of these papers, one particular disease is being detected. However, there is no such model which can detect all the common skin diseases through image processing. Furthermore, none of the papers have included instant solutions and suggestions regarding the treatment after successfully detecting the disease. On the other hand, some disease models only exist from a human perspective. However it is necessary for the farmers to take immediate action accurately right after the disease detection.

Chapter 3

Workflow

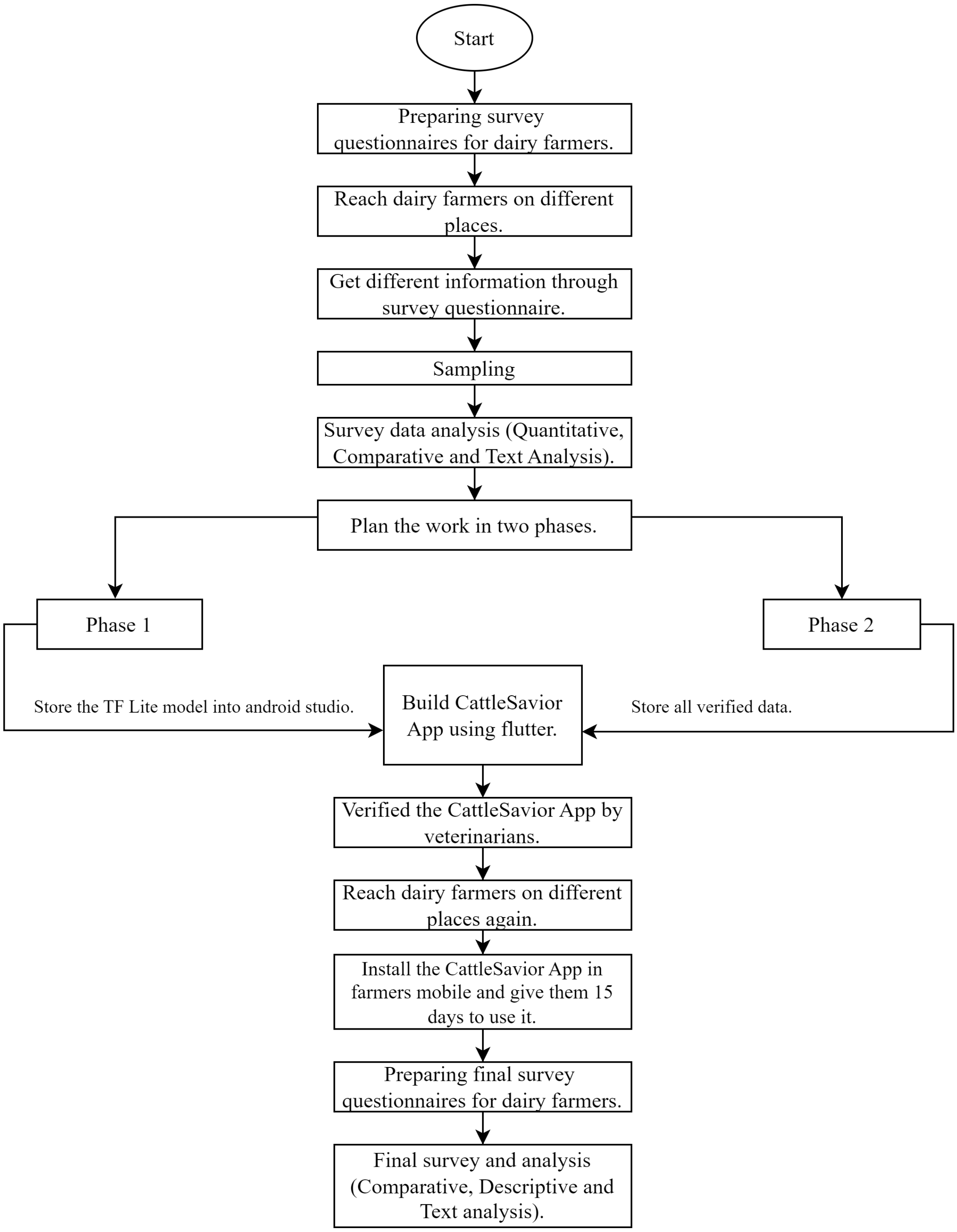


Figure 3.1: Overall workflow

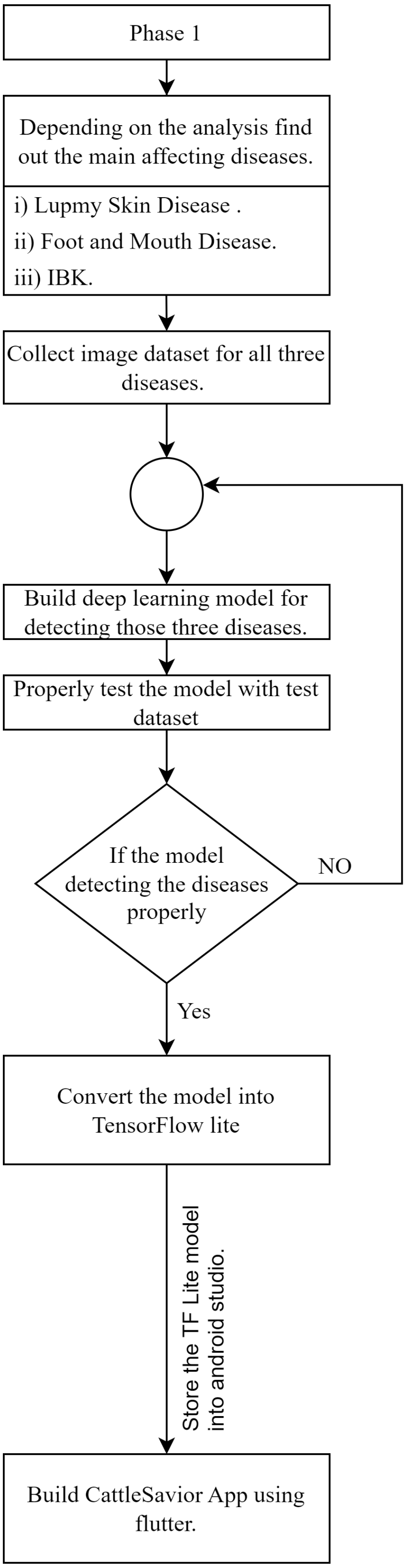


Figure 3.2: Phase-1

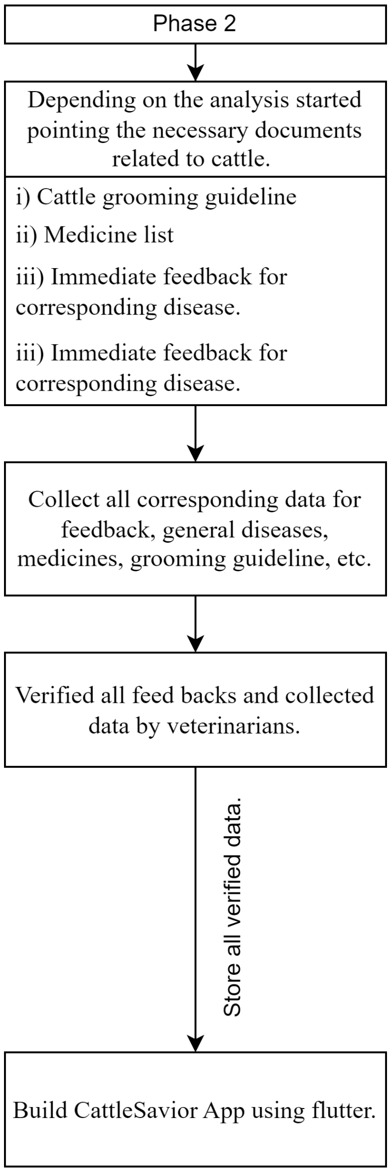


Figure 3.3: Phase-2

Chapter 4

Methodology

At the initial stage of our work, we mainly have to know about the thinking and needs of cattle farmers through our work. For that, we have to communicate and collect the true perception of the current situation. And here we can collect it as a form of survey dataset. So, to do the survey, first, we make a questionnaire for the survey and then do the in-person survey by visiting the farms as a team.

4.1 Questionnaire

To start the whole process of the survey we have to have a list of questions through which we can find out the data which we need to proceed and take our work forward. And there the list of the questions is basically the questionnaire for our survey. The questionnaire we have used is basically a structured type of questionnaire.

In our questionnaire, there were 26 questions in total and among those 26 questions most of the questions were close-ended (multiple choice questions) which denotes that the type of questionnaire is structured, but in our questionnaire, there are also some open-ended questions to get some opinions and suggestions from the farmers. From those 26 questions, there were 22 closed-ended and 4 open-ended questions in total. From all 26 questions, there were 2 quantitative questions from which we got numerical answers and the rest were 24 qualitative questions. For the questionnaire, we maintained the Likert slacking technique which goes under the high manipulation part. We did not add any questions that need any personal information except the name and phone number (here phone number was optional though) and on the open-ended questions we mainly asked for some personal opinion or suggestions for our application as our main aim to do the survey was to figure out the basic needs of farmers from our mobile applications and to know about their main problems more specifically.

4.2 Data Collection

At the beginning of our work, we want to know the present situation of the cattle farming domain. Therefore, we initiated our work by conducting a survey on the cattle farmers. For the survey, we have designed a questionnaire with 26 questions.

Moreover, we conducted the survey on *(N=13)* cattle farmers by in-person interview and *(N=13)* farmers via phone call. The in-person survey is conducted at Pandora, Vatara, Baliakandi of Savar and Kamarpara, Bhatulia, and Bamnartek of Uttara East Thana in Dhaka. The interview via phone call is conducted in different regions of the Brahmanbaria district. After the survey data collection, we follow two most efficient and popular analysis techniques which are Quantitative analysis and Qualitative analysis. Our work proceeds further depending on the end results of the survey.

4.3 Disease Detection

To detect the common external diseases (FMD, IBK, and LSD), we collect image datasets from different places for each disease [24], [29], [33] and create a merged dataset. After that, we explore different pre-trained (VGG-16, Inception-ResNet v2, Xception, DenseNet-121, Inception-v3) and custom CNN models with our dataset. In pre-trained models, we use transfer learning with data augmentation. In our proposed CNN model, we build with less amount of convolutional layers for good performance results.

4.4 App Integration

After getting our desired CNN model, we save our TensorFlow as a .h5 file. After that, we convert .h5 to a Tflite model and store it in Android Studio. Finally, we built our mobile app using Flutter. Our app can easily detect FMD, IBK, and LSD by uploading a picture of the affected area. Moreover, it also provides instant feedback for detected disease.

4.5 Feedback Collection

After developing the *'CattleSavior'* application, we get back to the respondents *(N=11)* of the first survey and install the application on their smartphones in accordance with their willingness. After 15 days, we returned with a questionnaire for the final survey to analyze the user satisfaction and their feedback. This final survey helps us to evaluate the successful implementation of the whole work.

4.6 Ethical Approval

The whole research is conducted according to the ethical sight in mind. From collecting and preparing the image dataset for deep learning models to conducting in-person interview surveys of the cattle farmers, all ethical points of view are strictly maintained. We capture the normal images of the cattle to complete the deep learning dataset with the permission of the cattle owner and make him aware of the purpose of collecting the images. All the information regarding the instant feedback after detection of a disease is collected from veterinarians. Also, we verify the whole application and every piece of information from multiple veterinarians. Further, in the survey with the cattle farmers, we have explained the whole purpose of our interview to them with the assurance that their data must remain private. Besides, we keep some personal data like contact numbers as optional in the questionnaire. For the installation of our 'Cattle Savior' application, we ensure the safety of their smartphone data and privacy, and the whole installation process is done with their permission and complete willingness. Furthermore, in the survey, all the photo, audio, and video recordings are conducted with the permission of the cattle farmer.

Chapter 5

SURVEY FINDINGS

5.1 Quantitative Analysis

From the survey questionnaires we have different statistical views from the cattle farmers.
As our mobile application runs on the Android operating system, it is very important to know if the cattle farmers have smartphones or not. So from the survey we get to know that 96.15% farmers have smartphones and 3.85% do not have any, which denotes almost all farmers use smartphones as their primary device.

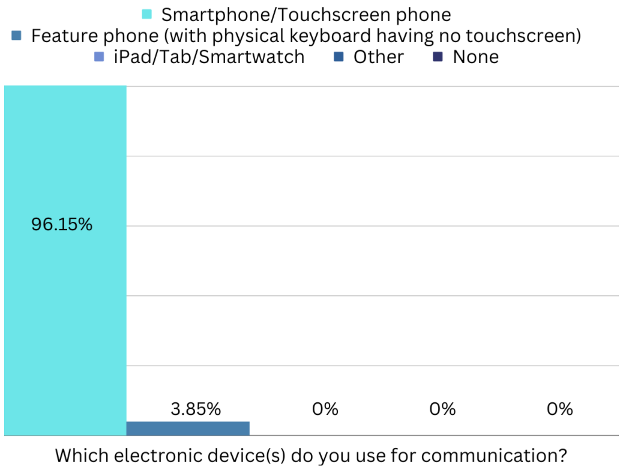


Figure 5.1: Which electronic device cattle farmer use

In addition, To detect the external disease accurately, we need the breeds of cattle which are more common in our country, for that we ask farmers through our survey which breed of cattle they mainly have in their farms. From there we get to know that 19.23% of total farmers have Bangladeshi local breed cows, 73.08% of them have Exotic breed (Holstein and Friesian / Sahiwal / Sindhi / Jersey), 19.23% have crossbreed cows in their farms and 0% farmers have other breeds.
Through the survey, we know about the total number of cattle from each farm (in Table 5.1).

Then, we check how often they face external diseases affecting the cattle in their farms. We get the answers like 15.39% farmers never face any problems of external

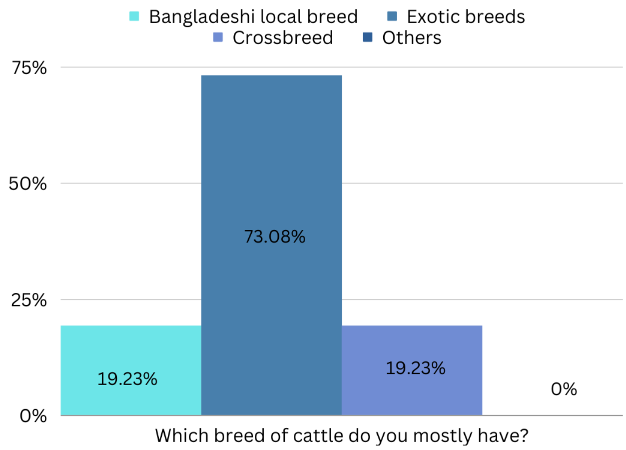


Figure 5.2: Which breed our cattle farmer use

Number of Cattles	Farms
2 to 10 cows	50%
11 to 20 cows	19.40%
21 to 40 cows	15.30%
41 to 117 cows	11.50%
118 cows	3.80%

Table 5.1: Number of Cattle on farms

diseases, 23.08% of them face the problem rarely, 19.23% farm owners face it sometimes, 23.08% of total farmers face it often and finally, the percentage of farmers who always face the external diseases are 23.08%.

We also want to know which external disease affects the most, then for Lumpy Skin Disease (LSD) 73.08% farmers agree that they face it in their farms most. Also 30.77% of them face IBK, 11.54% face Dermatological problems and 57.7% of total farmers face Foot and Mouth Disease (FMD) and there are 11.54% of farmers who face other diseases.

Here also we get to know When cattle are most vulnerable to external diseases. Here for 53.85% farms, it is the newborn cattle, in 73.07% farms adult cattle get affected, 15.39% farmers see cattle get affected by when they are in the pregnancy period, and finally, 53.85% of total participants agreed that their cattle get affected by external diseases when they are matured (age is more that 5 years).

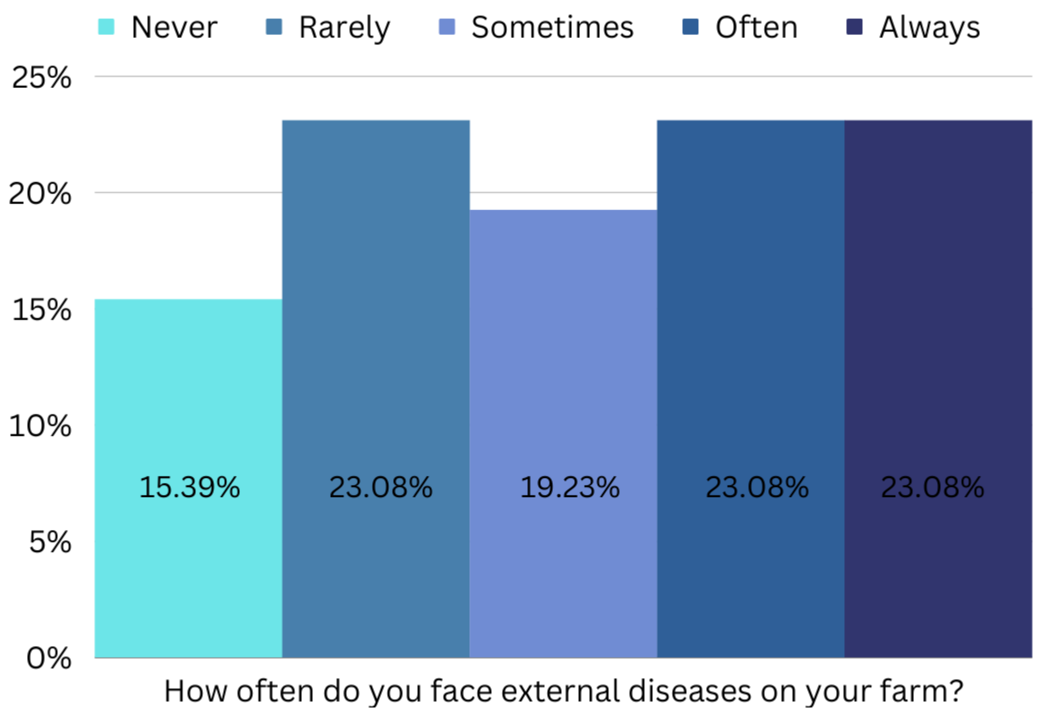


Figure 5.3: Percentage of facing external disease

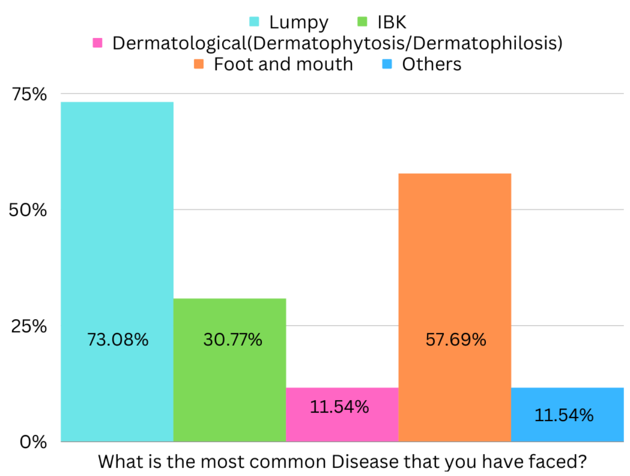


Figure 5.4: Percentage of common disease

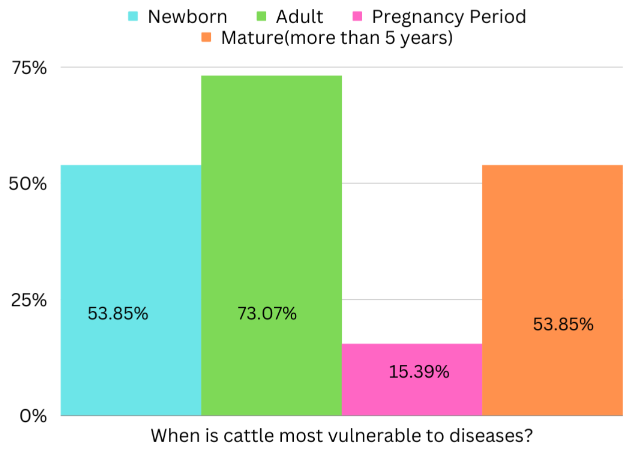


Figure 5.5: Percentage of most vulnerable disease

At the time when we need to know how often they can detect the external disease by themselves we get that 19.2% farmers rarely can detect the disease, 26.9% participants can detect the disease sometimes, 7.7% farm owner can detect the disease often and 46.2% of total farmers can detect the disease always.

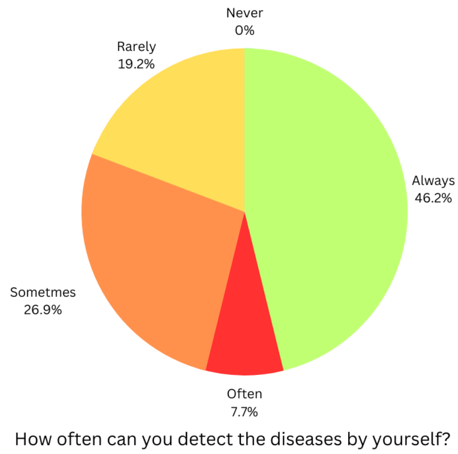


Figure 5.6: Percentage of detecting disease by own-self

Then we discuss how likely they consult with veterinarians for disease affected cattles, 61.5% farm owners state that they consult with veterinarians almost always, 11.5% of total state that they consult with veterinarians usually, 26.9% farmers state that they consult with veterinarians occasionally.
Also from the survey here we get to know about how likely they find the immediate solutions 42.3% of total farmers state that they get the solution always, 15.4% state that they get the solution often, 19.2% farm owners state that they get the solution sometimes, 11.5% get the solution rarely, and rest 11.5% farmers never get the immediate solution.
We also explore the use of smartphones for cattle diseases, from it 80.8% of total farmers say they never use smartphones for cattle disease 3.8% said rarely, 3.8% farmers always use , 3.8% farm owners use often and the rest 7.7% use sometimes.

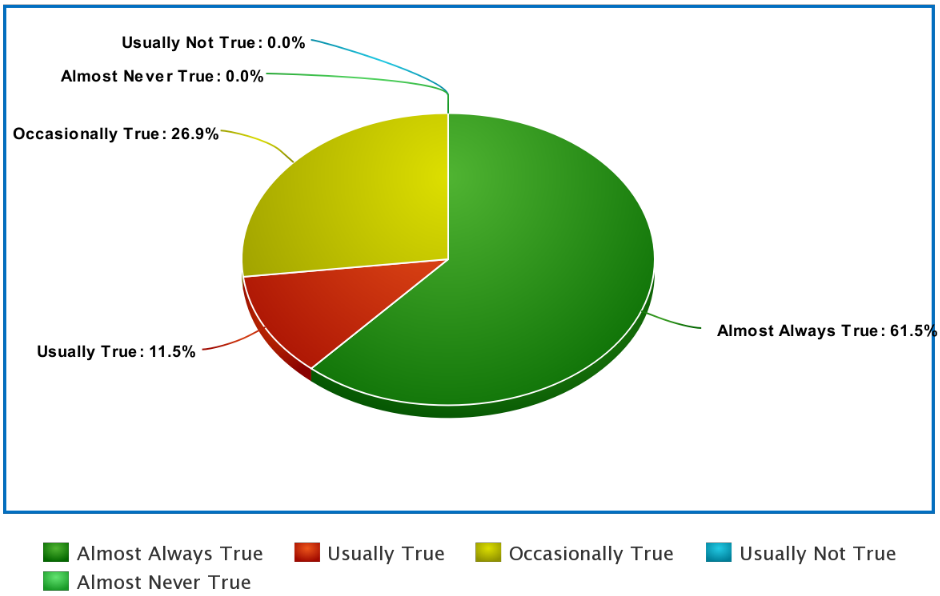


Figure 5.7: Percentage of consult with veterinarians

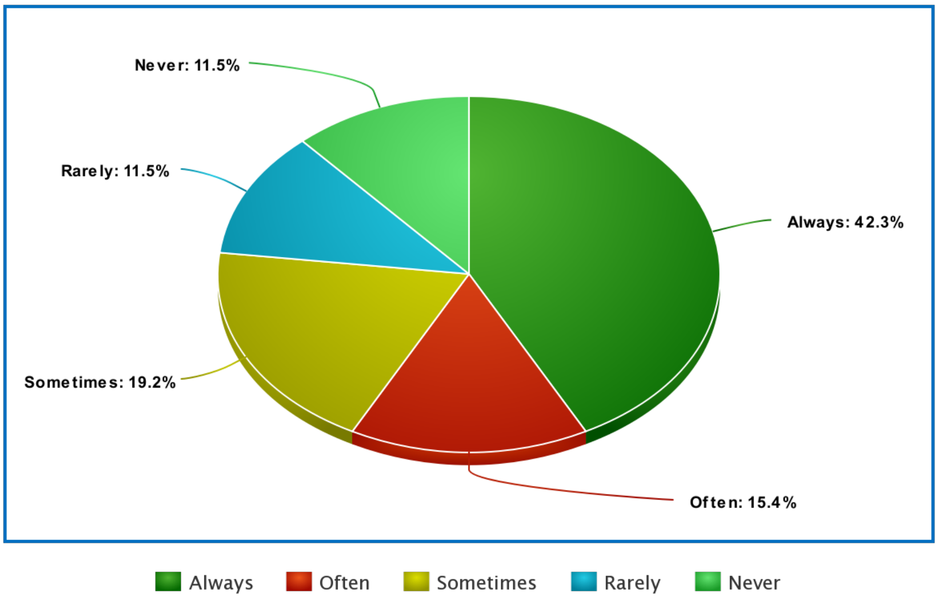


Figure 5.8: Percentage of getting immediate solutions

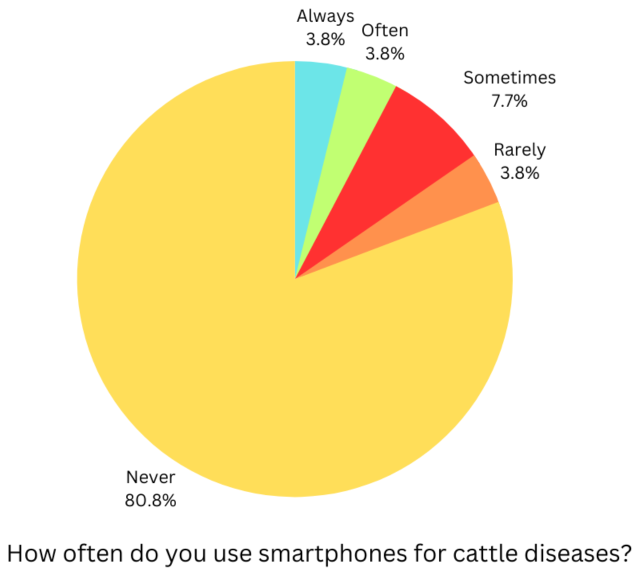


Figure 5.9: Percentage of using smartphone

Here we get to know that 46.15% farmers agree that external diseases become deadly, 26.92% strongly agree that it becomes deadly, 19.23% disagree that external diseases become deadly and the rest 7.69% farmers are undecided.

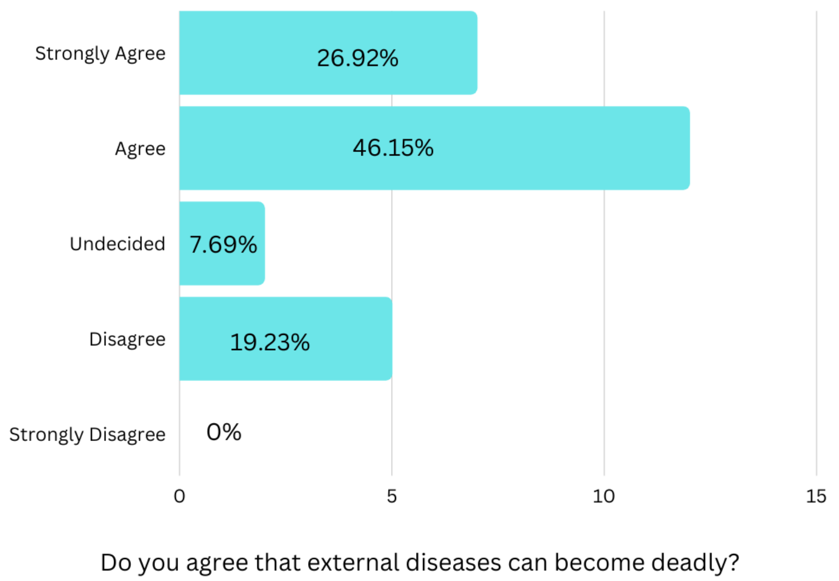


Figure 5.10: Percentage of external disease becoming deadly

We want to know about the approximate cost of treatment for a diseased cattle and farmers state that 34.6% of total farmers spend more than 4000 taka, 23.1% farmers spend 1000-1999 taka, 19.2% spend 2000-2999 taka and rest of them spend 3000-4000 taka which is 23.1%.

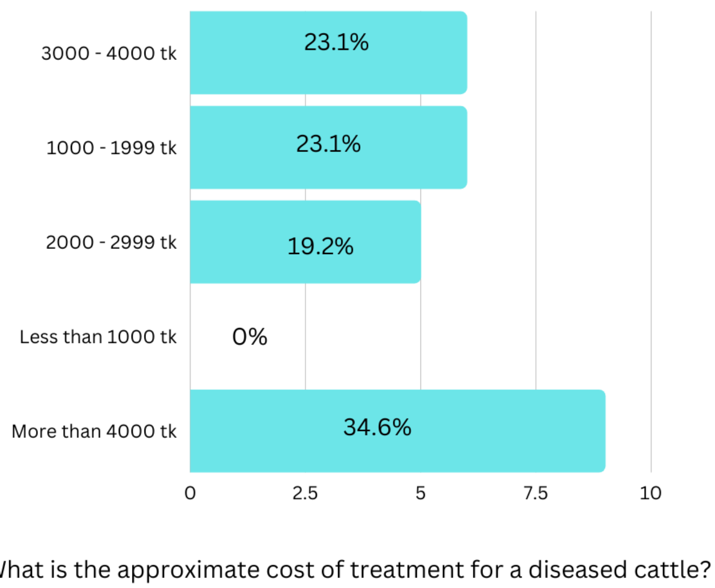


Figure 5.11: Percentage of approximate cost of a diseased cattle

About economic loss for cattle diseases 96.2% farmers strongly agreed that cattle external diseases bring significant economic loss.

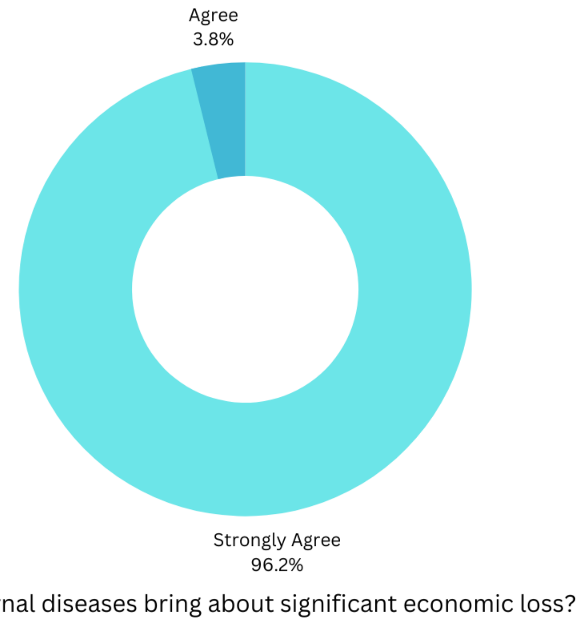
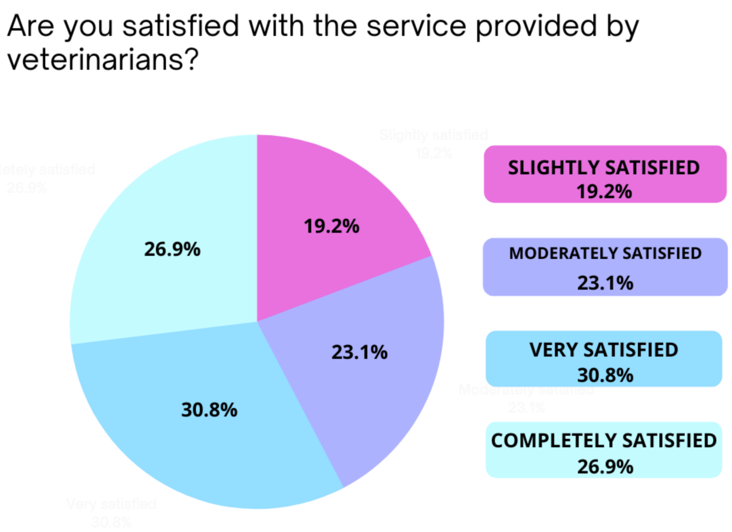
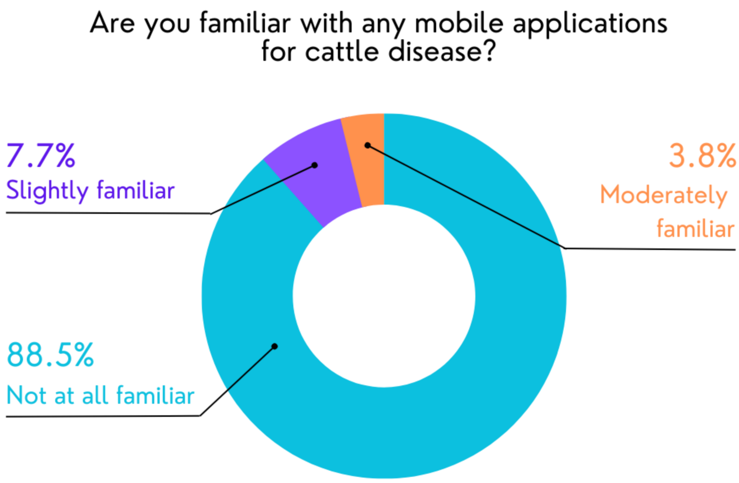


Figure 5.12: Percentage of economic loss for external disease

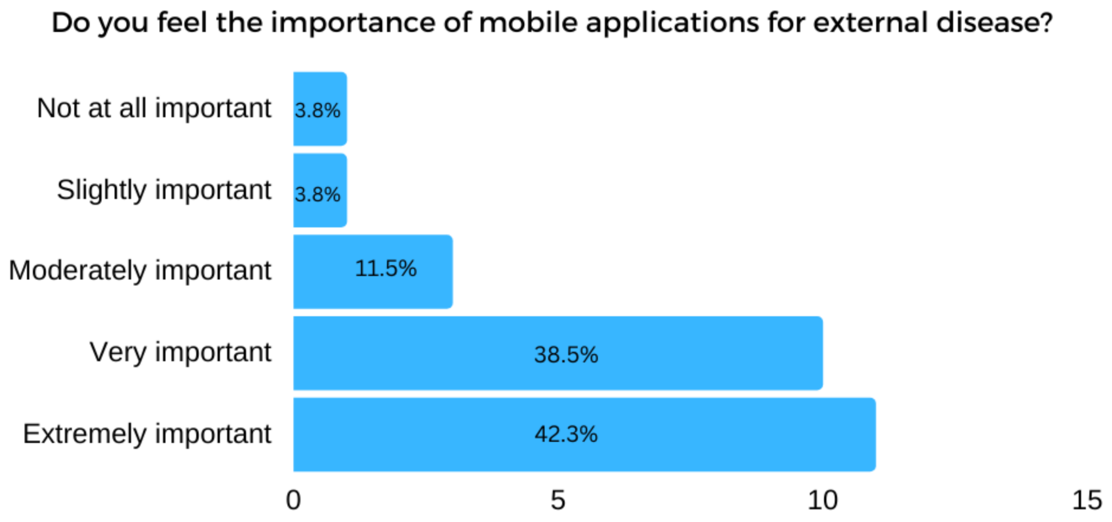
In addition, about the satisfaction with the service provided by veterinarians. So here at this point 30.8% farmers are very satisfied, 26.9% are completely satisfied, 26.9% of total farmers are moderately satisfied and finally 15.4% of total participants are slightly satisfied with the service of veterinarians.



At the time when we need to know that if they are familiar with any mobile application for cattle diseases, 88.5% of total farmers are not at all familiar, 7.7% of them are slightly familiar, and 3.8% are moderately familiar.

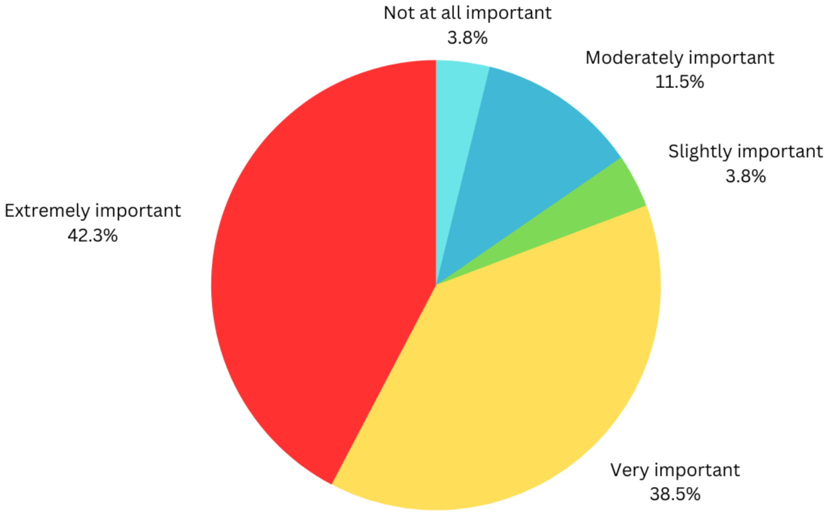


In addition, 3.8% farmers thought it is not important at all, 42.3% think it is extremely important, 38.5% of total farmers think it is very important, 3.8% farm owners think slightly important and the rest 11.5% think it is moderately important.



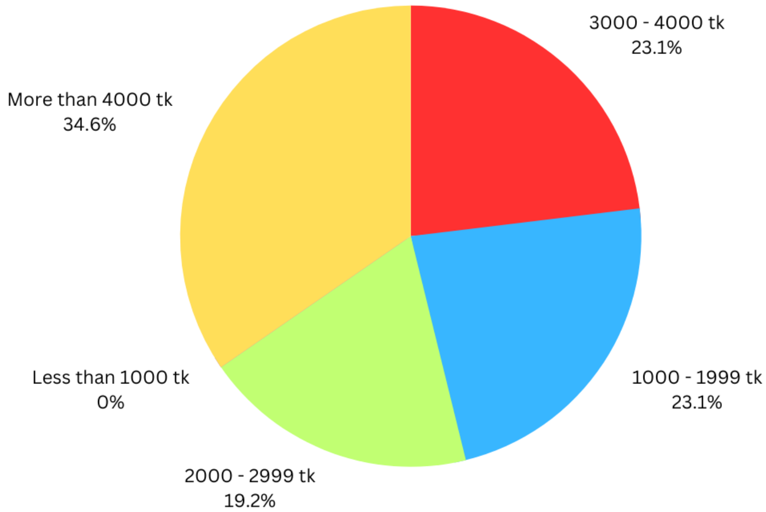
5.2 Comparative Analysis

Here at this part there is some comparison of answering the questionnaire depending on the experience in this cattle farming field.

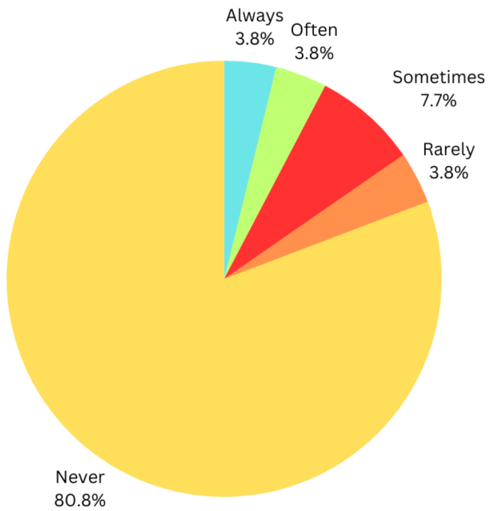


Do you feel the importance of mobile applications for external disease?

Because at that part when the questionnaire ask for the importance of a mobile application for detecting the external diseases and give solutions 3.8% farmers thought it is not important at all and where is 42.3% think it is extremely important and 38.5% of total farmers think it is very important, here the difference came because of the experiences of that 3.8% farmers. Because after discussing with them we get to know that maximum times they detect the diseases by themselves.
Because here 34.6% of farm owners spend more than 4000 taka, 23.1% farmers spend 1000-1999 taka, 19.2% spend 2000-2999 taka and the rest of them spend 3000-4000 taka which is 23.1%.



What is the approximate cost of treatment for a diseased cattle?



How often do you use smartphones for cattle diseases?

Besides 80.8% of total farmers say they never use smartphones for cattle disease 3.8% said rarely, 3.8% farmers always use , 3.8% farm owners use often and the rest 7.7% use sometimes.

So by compressing the detection process into a smartphone it will make the whole process very cost effective and also digitized.

5.3 Text Analysis

Here at this point we analyze the open-ended questions answers. During the survey we asked the farmers for any type of suggestions and opinions. From there we get to know that most of them gave some suggestions for our mobile app through which we can help them more. Like, most of them asked for cattle grooming guidelines for multiple breeds through which they can get to know about how to maintain and grow a cow up from a very young age to matured age level. So that they can improve the milk production, ensure good health conditions, breeding of cattle and many more. The farmers were interested about the instant feedback which could be given right after the detection of the external diseases. So, through those feedbacks they will get to know about the necessary steps for that particular disease and take them place on the spot. Also many of the farmers were interested about the medicine list for multiple diseases, because as a new cattle farmer it is very much important to know the exact uses of a particular medicine.

5.4 Probable Solution(s)

By doing the survey we got to know about the current situation in this field of external diseases detection and their solution providing system. So, after the survey was done, we started analyzing the questionnaire answers given by the cattle farmers. We did the analysis in some different perceptions and tried to figure out the problem so that finding the relatable solution became easy and appropriate for the users. After analyzing the survey outcome we divided the whole working process into three different segments or parts. Part one works for building the Machine learning / Deep learning model; part two makes the basic structure of the features in mobile application, part three collects the data for the other necessary documents like medicine list, cattle grooming guideline, etc.c. The work of these three parts started simultaneously. For the part at first we got to know about the main three diseases which are affecting the cattle most in farms and they are Lumpy Skin Diseases (LSD), Foot and Mouth Diseases (FMD), Infectious Bovine keratoconjunctivitis (IBK). And then after we started collecting the image dataset for all of these three diseases because our aim is to detect external diseases through the picture of affected parts in cattle's body.The dataset was divided into four classes: Lumpy, FMD, IBK, Normal skin, after the collection of dataset we augmented the images and updated our dataset. After augmentation the total dataset became the dataset of 13,792 pictures which is the summation of those four classes . After collecting the dataset we started exploring the existing pre-trained models including the models which were mentioned in the literature review part and also working on the custom model in CNN architecture because there was no existing work where any team used a custom CNN model for detecting the diseases through pictures . We have explored VGG-19, inceptionv3, inceptionresnetv2, xception, mobilenet, resnet50, densenet121. After that we finally selected to use the custom model built on CNN architecture. We converted the model into TensorFlow lite so that we can implement the model into our application.

On the other hand from the survey analysis we got to know beside detecting the diseases the users also need some other facilities, for that reason we made some different features which are relatable and important for a farm owner like: Cattle grooming guideline: where a farmer get detailed grooming guideline for a cattle from the very young age to mature age; Knowledge about general diseases: it is an static page for different different diseases separately from where a farmer easily can find and get to know about the common diseases name, reasons, clinical signs, preventions, treatments etc. ; Medicine list: where farmers can find the medicine list for multiple external and internal cattle diseases and also can do cross check if the suggested medicine by someone is appropriate for that particular disease or not; Vaccination details: where farmer can find vaccination name, place to push the vaccine, vaccine's precautions and usage for specific diseases; The reminder system for vaccination: so that farmers can track the date to give vaccine and get notification from the mobile application for vaccination; Veterinarians details: where farmers can find out the name of veterinarians, contact numbers, hospital location etc.

Now making the features are not enough, we need to implement those features with accurate and appropriate data which have to be verified by the veterinarians. So, we started collecting data from the veterinarians. We were continuously connected with more than 10 veterinarians during this data collection and verifying process who are assigned to different veterinary hospitals. We collected all the data like vaccine names, medicine names, vaccination time schedules for specific diseases, cattle grooming guidelines, etc., and also crosscheck all the information with all veterinarians so that there be no mistakes in that information because all this information is very sensitive for a cattle's life, breeding, milk production, if there is any single mistake it can harm the cattle in very bad way also it can be deadly for cattle. With all this kept in mind, we verified and cross checked all the information multiple times.

After verifying all the information, building the deep learning model, creating necessary features we stored all of them into android studio. After that we got our final application, then we started to test if all the features are working properly or not and more specifically the disease detection feature, because this is the most important part, if it gives output wrong that could create a very bad consequence for farming and cattle's life. We tested randomly with the picture of affected and healthy cow skin and eyes and the output were tremendously perfect. In the perspective of our survey our app is covering the most common external diseases like, Lumpy skin Disease (LSD) which is 73.1% of the total farmers faced in farms, Foot and Mouth Disease (FMD) which is 57.7% of the total farmers faced in farms, IBK which is 30.8% of the total farmers faced in farms.

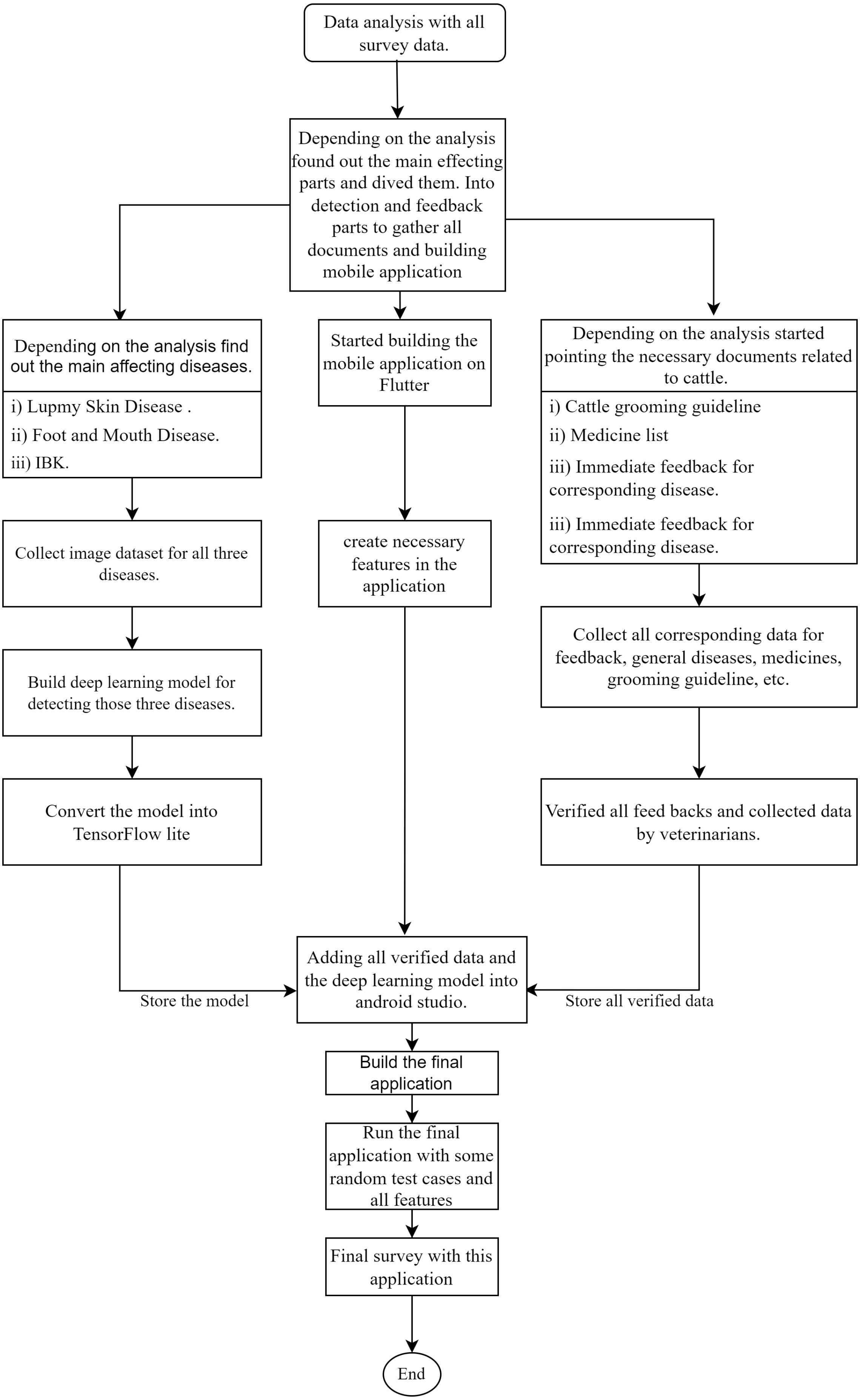


Figure 5.13: Solution Planning

Chapter 6

MODEL DESIGN AND IMPLEMENTATION

6.1 Dataset Collection

6.1.1 Lumpy Skin Disease(LSD) Dataset

For different Deep learning model analyses, the initial image dataset has been collected from the Mendeley Dataset[28], which is a dataset of Lumpy skin disease. This was a dataset with two classes Lumpy skin and Normal skin. In this dataset, there are 1024 images in total where 324 images are LSD and the rest are normal skin. The image size of all those images is 256*256 and all images are colored images. Across the total dataset with 1024 images most of the images were captured by mobile phones or smartphones and also the picture quality of some of the images was not that good. As many of the pictures are clicked through smartphones the angles of the pictures are not generalized or any angle has been maintained, so that there are some pictures in random orientations already.

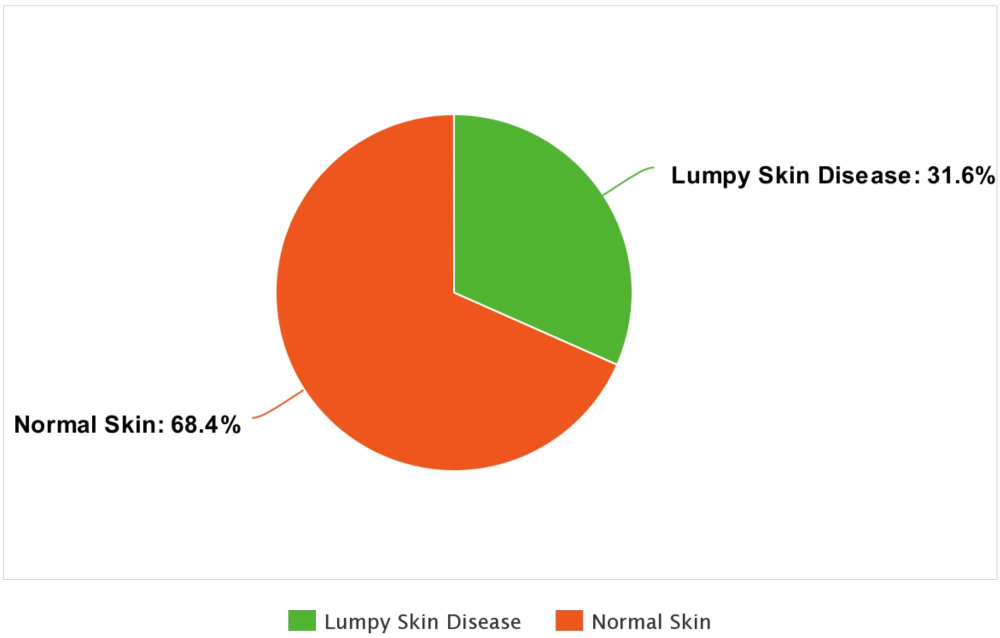


Figure 6.1: Lumpy Skin Disease Dataset

6.1.2 Foot and Mouth Disease(FMD) Dataset

We have collected foot and mouth disease dataset from Zenodo[], which was published in Mar 28, 2023 and an open access dataset. This dataset also has two classes (Foot and Mouth disease, Normal Skin). This dataset has 304 images where 156 images for foot and mouth disease and 148 images for normal skin. The image size of all images are 512*512 and all images are colored images. All these images were collected from different dairy farms and the internet. Since most of the pictures are clicked through smartphones, all the pictures are already in random orientations.

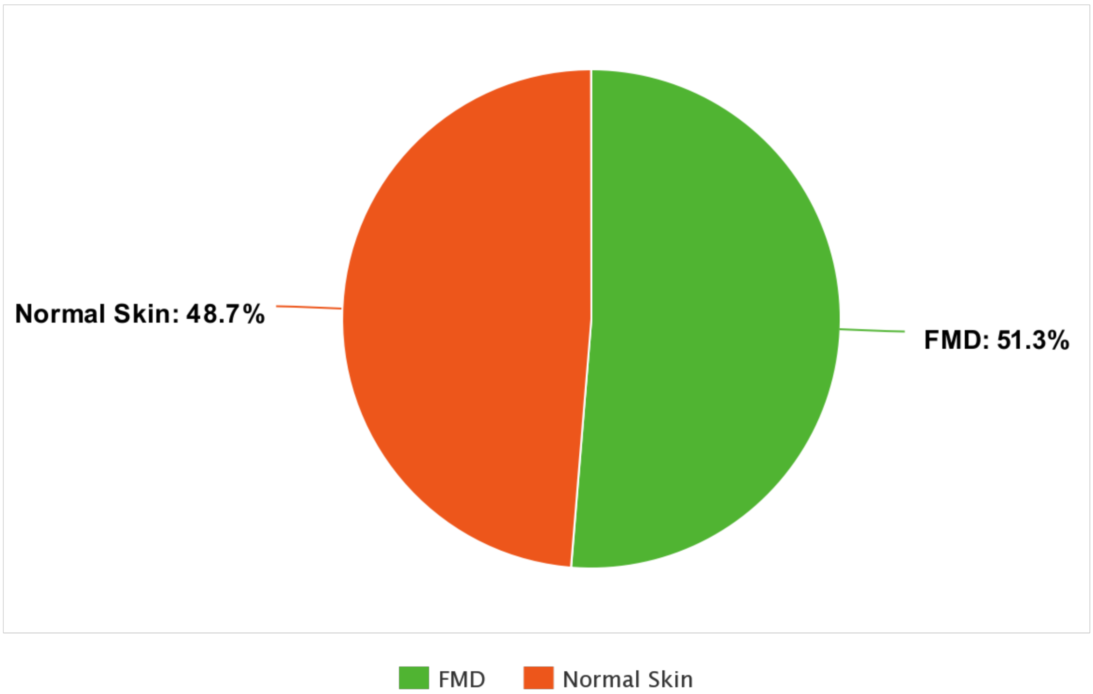


Figure 6.2: Foot and Mouth Disease Dataset

6.1.3 Infectious Bovine Keratoconjunctivitis(IBK) Dataset

We got only Infectious Bovine Keratoconjunctivitis data from Md. Rony et al.[23]. There were three classes for LSD, FMD, IBK. So, we got 150 IBK images from that dataset. Moreover, we have collected 150 images from different farms for Normal skin to differentiate between IBK and Normal Skin. The size and orientation of all the images are different.

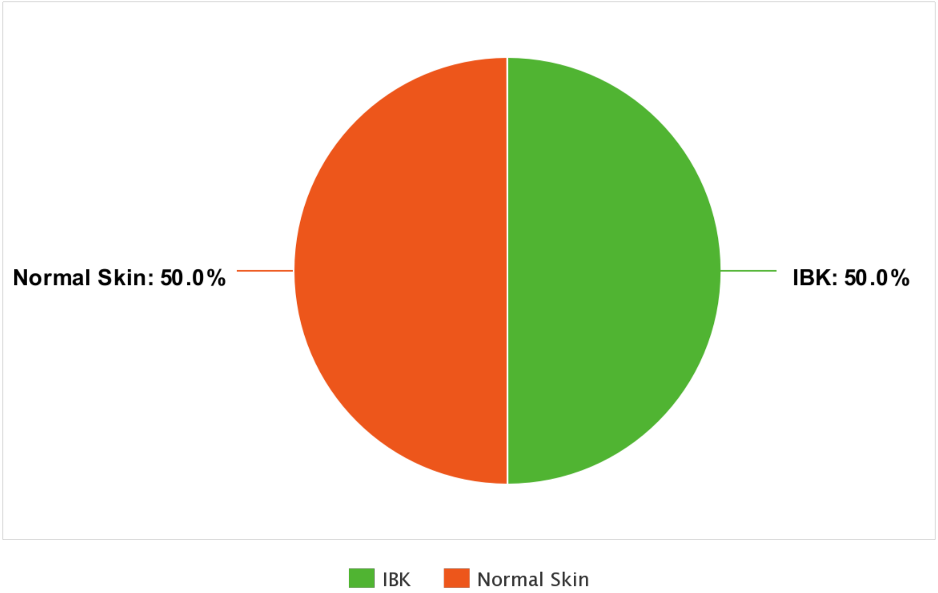


Figure 6.3: Infectious Bovine Keratoconjunctivitis Dataset

6.1.4 Final Dataset

As we want to build a model that can detect external disease (LSD, FMD, IBK) and Normal Skin of cattle, we merged our three datasets together into one dataset which has a total of four classes (LSD, FMD, IBK and Normal Skin). We have a total of 304 images in LSD class, 156 images in FMD class, 150 images in IBK class and 998 images in Normal class.

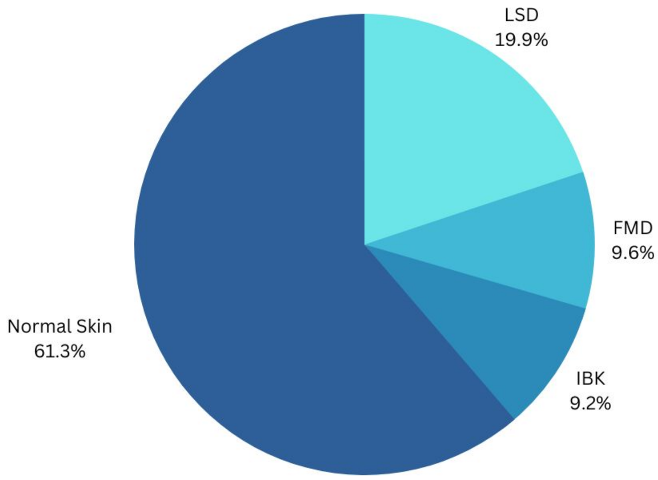


Figure 6.4: Final Dataset

Table 6.1: Number of Images in Dataset

Class Name	Number of Raw images	Number of Augmented images
FMD	156	2340
IBK	150	1978
LSD	304	2149
Normal Skin	998	7325
Total	**1608**	**13792**

6.2 Data Pre-processing

In our final dataset, we have a total of 304 images in LSD class, 156 images in the FMD class, 150 images in the IBK class, and 998 images in the Normal Skin class. Here, we can clearly see that the number of images is really low. Since it is a small dataset, we decided to use data augmentation in our dataset to increase the number of images. Data augmentation is a necessary step as our dataset is small. It will help us to generate a big dataset using that small dataset and help us to reduce overfitting in our deep learning neural network model. There are different types of data augmentation techniques available such as rotating, shifting, zoom and so on. For Data augmentation, we have used horizontal flip, width shift range=0.2, height shift range=0.2, brightness range[0.1,0.3], zoom range=0.2, fill mode='nearest'. We generated 8 or 9 images from each image and now we have a total of 13792 images. In our augmented dataset, we have 2340 FMD data, 1978 IBK data, 2149 LSD data, and 7325 Normal Skin data (in Table 6.1).

6.3 Dataset Split

We split our final dataset into three parts - train, test, and validation. We store 70% dataset for our training data, 10% for testing data, and 20% for validation data.

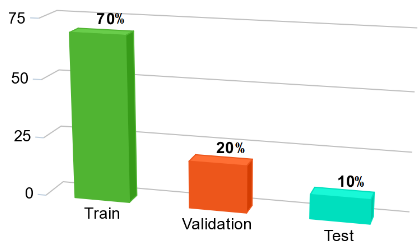


Figure 6.5: Train, Validation, Test data split

6.4 Proposed CNN Model

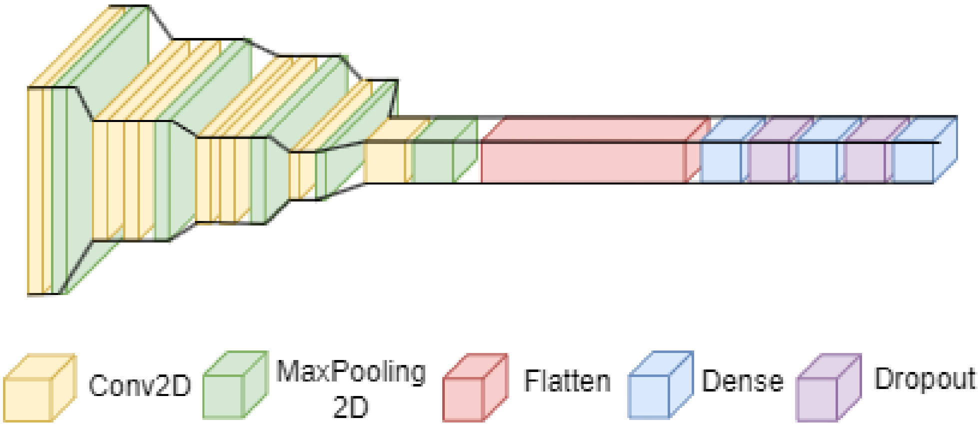


Figure 6.6: Proposed CNN Architecture

CNN is a special artificial neural network designed to analyze visual data. Our CNN model is initiated by a Conv2D layer having an input shape of 224*224 with a filter size of 64. We use a total of seven Conv2D layers each of them has a kernel size of (3,3) and a default stride of (1,1). We use a Max Pooling Layer with (2,2) pool size. Furthermore, 20% dropouts are used in between dense layers to avoid overfitting problems. We chose the Relu activation function because of its easy computational ability. It introduces non-linearity to the model and its gradient is not saturated which allows learning complex patterns easily compared to Tanh and Sigmoid function. Then, we convert the values to a one-dimensional array with the help of a flattened layer. Lastly, we add two dense layers of 128 nodes where dropout layers are added in between those two. Additionally, we use Adam optimizer to maximize the effectiveness of our model with a learning rate of 0.001. In the output layer, we use Softmax classification to classify the network. It categorizes all nodes and converts the raw scores into a probability distribution to make the decision-making process easier. Moreover, we run the model up to 50 epochs with a batch size of 32. The complete structure of the custom CNN model is demonstrated in Table 6.2 and visually represented in Figure 6.6.

6.5 Related CNN Models

However, we have also explored different pre-trained and hybrid models such as VGG-16, Inception-ResNet v2, Xception, DenseNet-121, and Inception-v3. Our primary goal is to get a good performance model with fewer parameters. We also have tried to reach our goal through pre-trained models by using transfer learning.

6.5.1 VGG-16

As we know VGG16 is a pre-trained CNN model but here we have used transfer learning with data augmentation. At first, we create the base model by using VGG16 where we use the include top argument as false(if include top is false, the fully connected output layers of the pre-trained model do not load initially to make any predictions), weight = 'imagenet' and provide our images as 224*224*3 size. In the

Table 6.2: Output Shape and Parameter Size of the Custom CNN Model

Layers	**Output Shape**	**Parameters**
2D Convolutional Layer	(32, 224, 224, 64)	1792
2D Max Pooling	(32, 112, 112, 64)	0
2D Convolutional Layer	(32, 112, 112, 32)	18464
2D Convolutional Layer	(32, 112, 112, 32)	9248
2D Max Pooling	(32, 56, 56, 32)	0
2D Convolutional Layer	(32, 56, 56, 32)	9248
2D Convolutional Layer	(32, 56, 56, 32)	9248
2D Max Pooling	(32, 28, 28, 32)	0
2D Convolutional Layer	(32, 28, 28, 64)	18496
2D Max Pooling	(32, 14, 14, 64)	0
2D Convolutional Layer	(32, 12, 12, 128)	73856
2D Max Pooling	(32, 6, 6, 128)	0
Flatten	(32, 4608)	0
Dense	(32, 128)	589952
Dropout	(32, 128)	0
Dense	(32, 128)	16512
Dropout	(32, 128)	0
Dense	(32, 4)	516
Total parameters	747,332	
Trainable parameters	747,332	
Non-trainable parameters	0	

second step, we add a custom classification layer on top of our base model. Here, we add a GlobalAveragePooling2D layer after our base model output. Then we add three dense layers where we can make predictions from the last dense layer. We also use a Dropout layer with 0.6 dropout in between every two dense layers to reduce the overfitting of the model. After that, we create a model where we provide the base model as input and predictions as output. In the third step, we froze the layers of the pre-trained model where we mark every layer in the base model as False. In the fourth step, we compile our model. We use Adam as an optimizer where we select the learning rate as 0.0001. We also use loss='categorical crossentropy' and accuracy as a matrix. In the final step, we train the model by providing our train and validation images. Here, we have used 50 epochs to get the best outcome from VGG16 (in Figure 6.7).

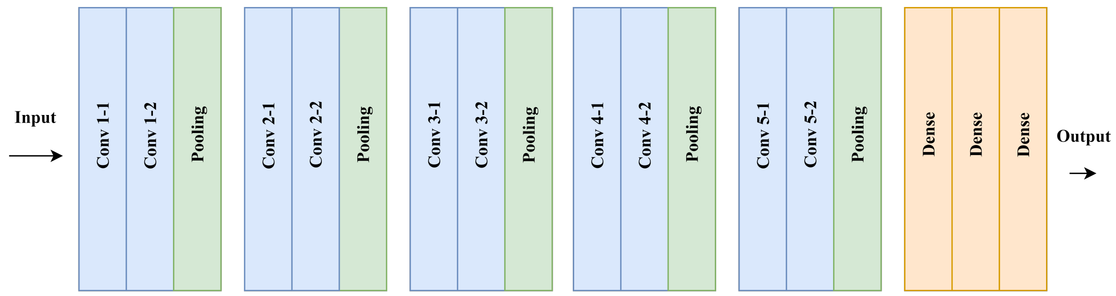


Figure 6.7: VGG16 Architecture

6.5.2 Inception-ResNet-v2

Inception-ResNet-v2 was created by Christian Szegedy, Sergey Ioffe, and Vincent Vanhoucke from Google's AI team in 2016. It is a hybrid model that combines Inception's multi-layer feature extraction with ResNet's skip connections. At first, we create the base model by using InceptionResNetV2 with an input size of 299*299*3. In the second step, we add a custom classification(GlobalAveragePooling2D) layer on top of our base model. Then we add three dense layers where we can make predictions from the last dense layer. We also use a Dropout layer with 0.2 dropouts in between every two dense layers to reduce the overfitting of the model. After that, we create a model where we provide the base model as input and predictions as output. In the third step, we froze the layers of the pre-trained model where we mark every layer in the base model as False. In the fourth step, we compile our model. We use Adam as an optimizer where we select the learning rate as 0.001. We also use loss='categorical crossentropy' and accuracy as a matrix. In the final step, we train the model by providing our train and validation images. Here, we have used 50 epochs to get the best outcome from Inception-ResNet-v2 (in Figure 6.8).

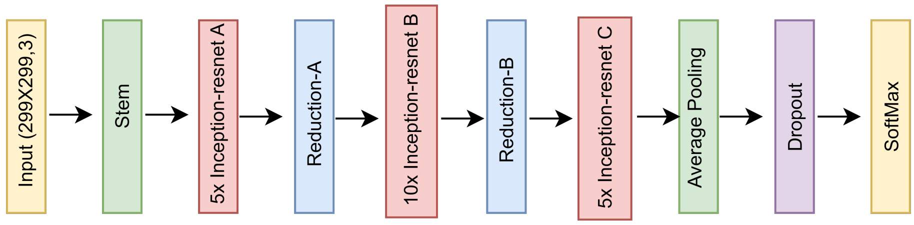


Figure 6.8: Inception-ResNet-v2 Architecture

6.5.3 Xception

Xception is a pre-trained CNN model that performs well on the ImageNet dataset. Here, we create the base model by using xception with an input size of 299*299*3. In the second step, we add a custom classification(GlobalAveragePooling2D) layer on top of our base model. Then we add three dense layers where we can make predictions from the last dense layer. We also use a Dropout layer with 0.5 dropouts in between every two dense layers to reduce the overfitting of the model. After that, we create a model where we provide the base model as input and predictions as output. In the third step, we froze the layers of the pre-trained model where we mark every layer in the base model as False. In the fourth step, we compile our model. We use Adam as an optimizer where we select the learning rate as 0.001. We also use loss='categorical crossentropy' and accuracy as a matrix. In the final step, we train the model by providing our train and validation images. Here, we have used 50 epochs to get the best outcome from Xception (in Figure 6.9).

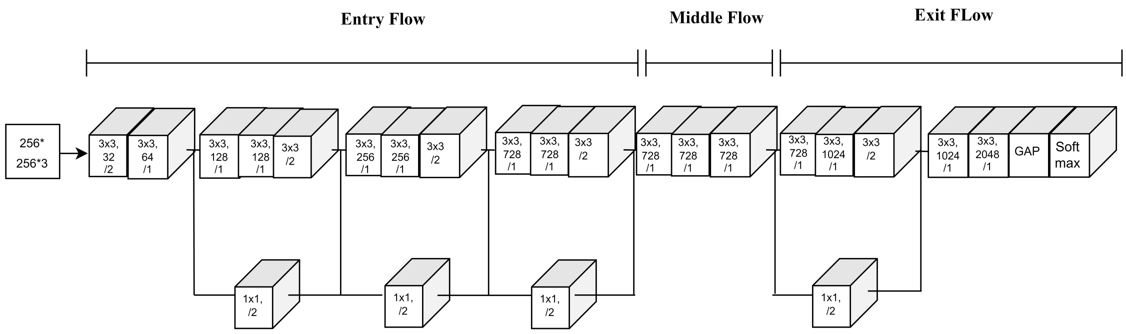


Figure 6.9: Xception Architecture

6.5.4 DenseNet-121

DenseNet-121 is a CNN architecture which is developed by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger. Firstly, we create the base model by using DenseNet-121 with the input size of 299*299*3 . In the second step, we add a custom classification(GlobalAveragePooling2D) layer on top of our base model. Then we add three dense layers where we can make predictions from the last dense layer. We also use a Dropout layer with 0.5 dropout in between every two dense layers to reduce the overfitting of the model. After that, we create a model where we provide the base model as input and predictions as output. In the third step, we froze the layers of the pre-trained model where we mark every layer in the base model as False. In the fourth step, we compile our model. We use Adam as an optimizer where we select the learning rate as 0.001. We also use loss='categorical crossentropy' and accuracy as a matrix. In the final step, we train the model by providing our train and validation images. Here, we have used 50 epochs to get the best outcome from DenseNet-121 (in Figure 6.10).

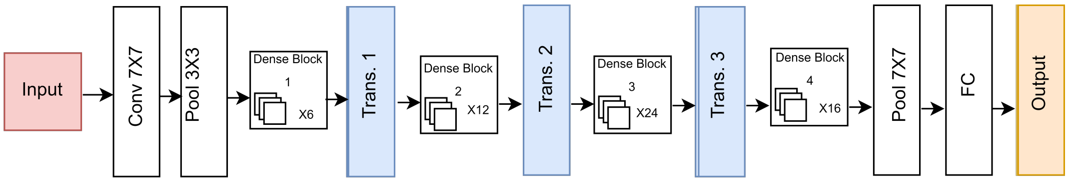


Figure 6.10: DenseNet-121 Architecture

6.5.5 Inception-v3

Inception-v3 is also a pre-trained dataset with 42 layers. Here, we create the base model by using Inception-v3 with an input size of 299*299*3. In the second step, we add a custom classification(GlobalAveragePooling2D) layer on top of our base model. Then we add three dense layers where we can make predictions from the last dense layer. We also use a Dropout layer with 0.5 dropouts in between every two dense layers to reduce the overfitting of the model. After that, we create a model where we provide the base model as input and predictions as output. In the third step, we froze the layers of the pre-trained model where we mark every layer in the base model as False. In the fourth step, we compile our model. We use Adam as an optimizer where we select the learning rate as 0.001. We also use loss='categorical crossentropy' and accuracy as a matrix. In the final step, we train the model by providing our train and validation images. Here, we have used 50 epochs to get the best outcome from Inception-v3 (in Figure 6.11).

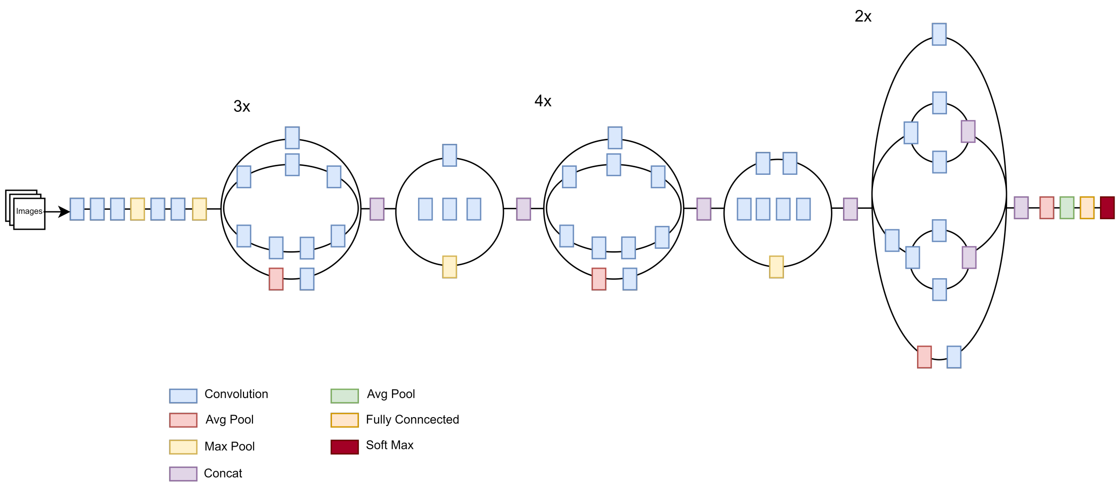


Figure 6.11: Inception-v3 Architecture

6.6 Deep Learning Model Results

We have tested and explored several pre-trained CNN models and our proposed CNN model with our dataset. Here, we use accuracy, precision, recall, F1, and loss measures as metrics for performance measurement in this study.

Accuracy is the most common performance measurement metric which can be defined as a proportion of the number of correct predictions and the total number of predictions. Mathematically this can be defined in terms of this formula:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100\% \tag{6.1}$$

Precision is used to figure out the accuracy of positive prediction of the model. This is calculated by dividing the total true positive outcomes (TP) by the number of total positive predicted outcomes (TP+FP). This can be shown by this equation:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{6.2}$$

Recall is another popular performance measurement metric that is used to measure the ability of the model by identifying the relative positive outcomes. This can be measured by dividing the total correctly predicted positive instances (TP) and total positive instances (TP+FP). Mathematically, recall is defined as,

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{6.3}$$

Likewise, f1 score is another performance measurement metric which shows a balanced evaluation of precision and recall score. It defines the effectiveness of a model. Also, f1 score is an arithmetic mean of precision and recall which can be demonstrated by the following equation:

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6.4}$$

6.6.1 CNN

From our custom CNN model, we get 97.4% train, 98% validation and 98.48% test accuracy. In terms of loss, we get 8% training and 10% validation loss.
From our confusion matrix, we can also see that it can predict 264 FMD class out of 267 true FMD class, 198 IBK class out of 203 true IBK class, 188 Lumpy Skin out of 190 true Lumpy Skin class and 564 Normal Skin out of 588 true Normal Skin class

6.6.2 VGG16

From our VGG16 model, we get 96.97% train, 94.17% validation and 98.48% test accuracy. In terms of loss, we get 8.5% training and 16.5% validation loss.

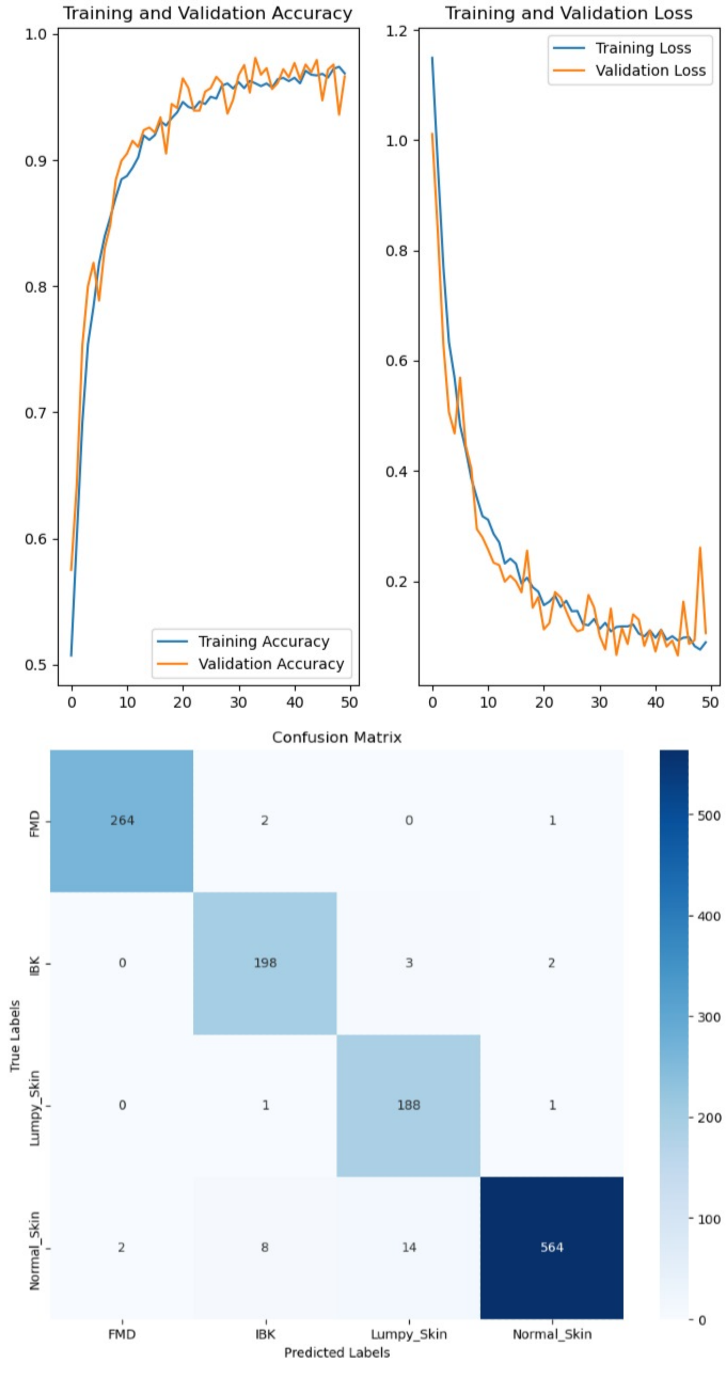


Figure 6.12: Accuracy, loss graph and confusion matrix

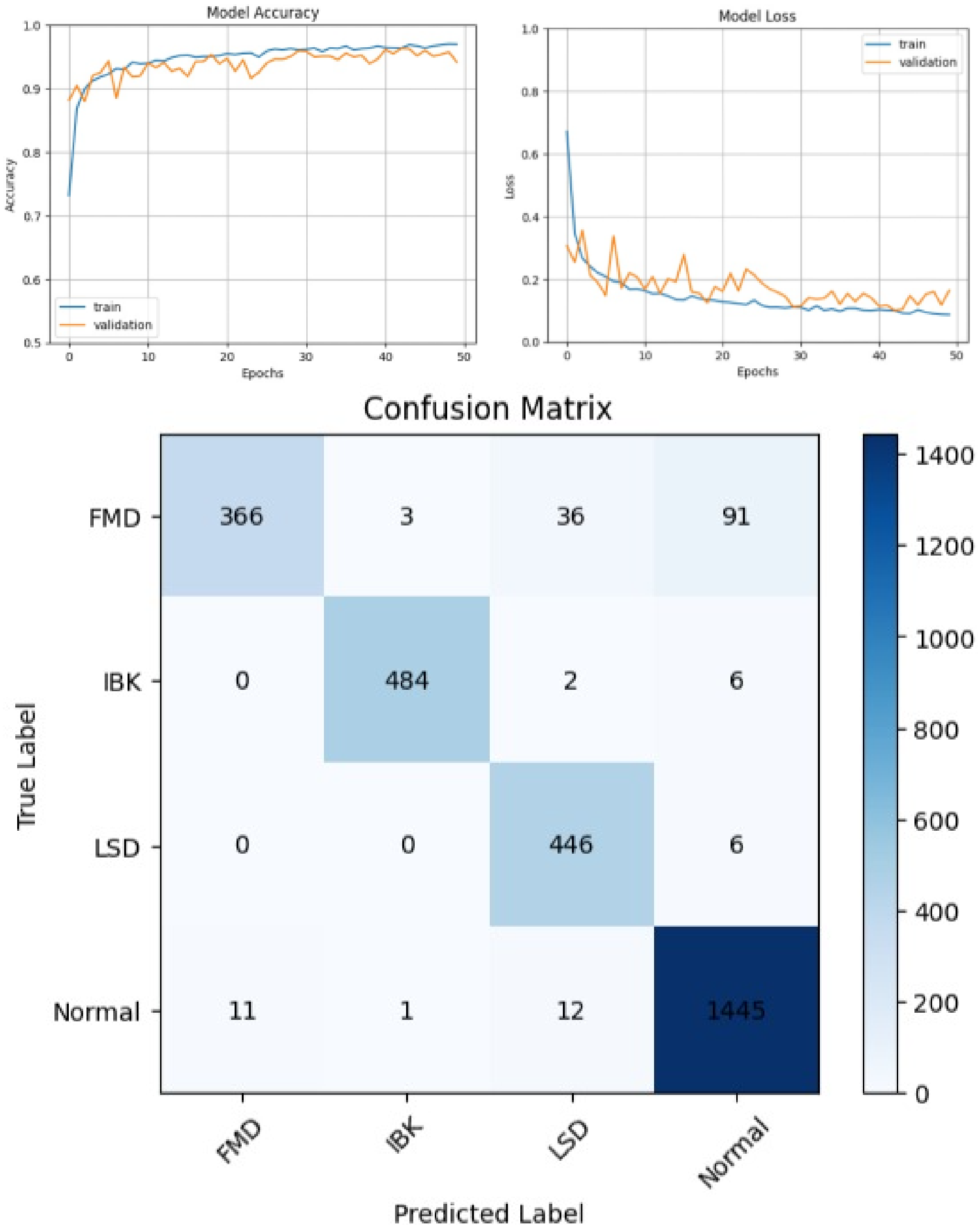
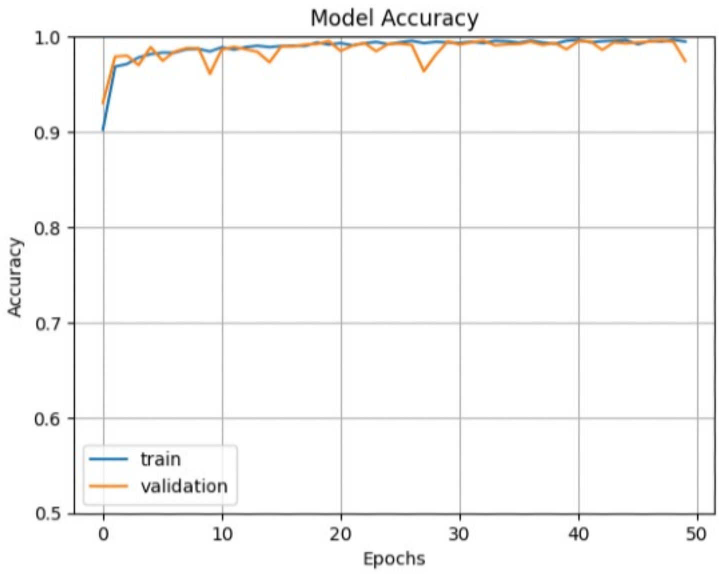


Figure 6.13: Accuracy, loss graph and confusion matrix

6.6.3 InceptionresV2

From our InceptionaresV2 model, we get 99% train, 97.4% validation and 98.48% test accuracy. In terms of loss, we get 1.5% training and 8% validation loss.



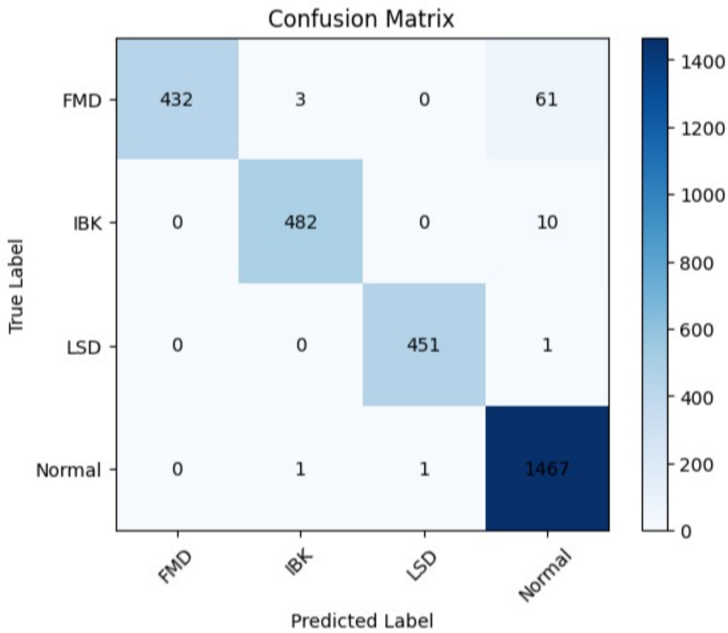


Figure 6.14: Accuracy, loss graph and confusion matrix

6.6.4 Xception

From our InceptionaresV2 model, we get 98.2% train, 98% validation and 98% test accuracy. In terms of loss, we get 5.5% training and 5.5% validation loss.

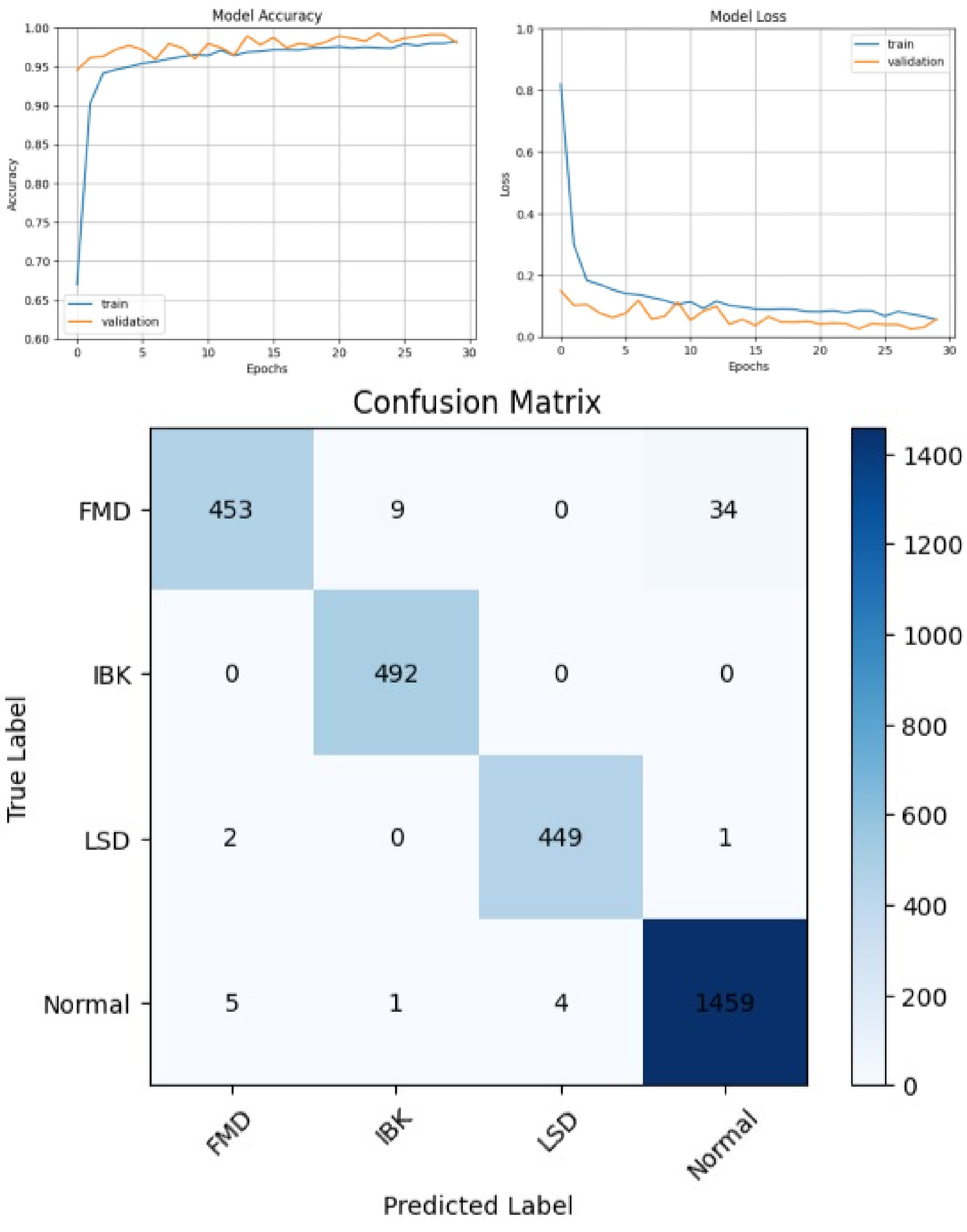


Figure 6.15: Accuracy, loss graph and confusion matrix

6.7 Comparison and Analysis

Table 6.3: Different Performance Metrics Comparison after Training Different Deep Learning Architectures

Deep Learning Architectures	**Parameters (in Millions)**	**Training Accuracy**	**Training Loss**	**Validation Accuracy**	**Validation Loss**	**Prec**
VGG-16	15.11	0.96	0.09	0.94	0.09	0.9
Inception ResNet v2	55.26	0.99	0.02	0.97	0.08	0.9
DenseNet-121	7.69	0.98	0.06	0.99	0.03	0.9
Inception v3	22.98	0.98	0.06	0.99	0.05	0.9
Xception	22.11	0.98	0.06	0.98	0.06	0.9
Ours	**0.75**	**0.99**	**0.04**	**0.99**	**0.04**	**0.9**

Table 6.4: Performance Metrics Comparison with Related Work

Author	**Method**	**Classes**
Genemo et al. **genemo2023detecting**	ELM	LSD, Normal Skin
Rony et al. [23]	GoogleNet	FMD, Normal Skin
Rony et al. [24]	Inception-v3	LSD, FMD, IBK
Ours	**CNN (Proposed)**	**LSD, FMD, IBK, Normal Ski**

Chapter 7

Final Survey

From the first survey, we get an idea about the overall cattle farming situation, different diseases and challenges of the farmers. Analyzing those, we feel the importance of using modern technology in this sector and providing them the right information at the right time in the palm of their hand without any cost. As from the first survey analysis, 96% of the cattle farmers use smartphones. What is a better way than an easy to use smartphone application to implement this idea.

After developing the 'CattleSavior' mobile application, we get back to the same cattle farmers to know their views on it. We install the application on their smartphones with a proper go throw demonstration of how all the features work. After 7 days, we return with a survey form to know their reviews and opinions on the mobile application. This is also an in-person survey where we ask questions in Bangla and fill the survey form according to the responses.

7.1 Questionnaire

The final survey consists of a total of 21 questions. Among these, there are 10 demographic questions which includes, Name, Gender, Age, Total Number of Cattles, Educational Qualification, Contact Number, Smartphone Model, Smartphone RAM, Smartphone ROM, Smartphone Price of the cattle farmers. The remaining 11 questions are about their experience and different thoughts on the application which includes 9 different 5 point likert scale questions and 2 open-ended questions. Here, 1 question covers the review of 8 different features of the application. And, 1 question is about the overall rating of the application. Among the 11 different responses of the hands on experience of the 'Cattle Savior' mobile application, 5 of them are in the area of Bishmaile, Pandoa, Savar, Dhaka and 6 of them are in Kamarpara, Bhatulia, Bamnartek of Uttara East Thana, Dhaka. Fig-6 shows different survey question types.

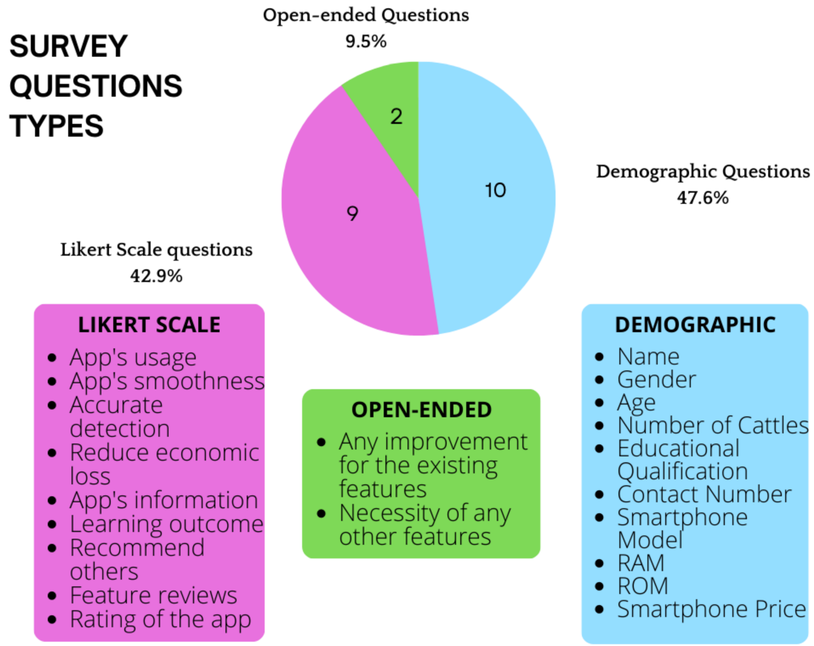


Figure 7.1: Survey questions types

7.2 Comparative Analysis

From the 11 cattle farmers, most of the cattle farmers are male. In comparison to 10 males, there is only one female cattle farmer in our survey. The figure-5 below shows the percentage of male and females along with their age comparison.

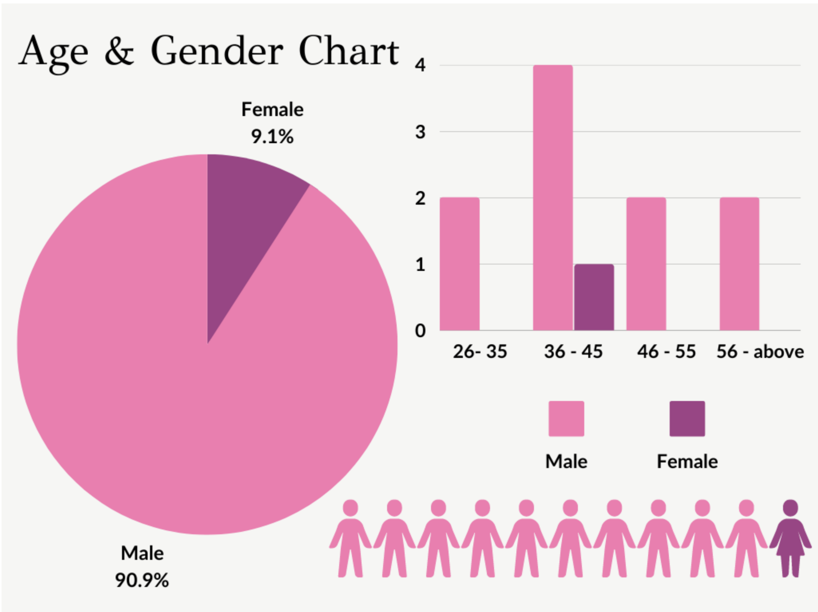


Figure 7.2: Age and Gender Chart of the survey participants

The figure shows that there are only 2 respondents between 26 to 35 years old. Whereas, a maximum of 5 respondents are between 36 to 45 years old and the only female respondent is in this age group. Then, 2 participants are in the age group 46 to 55, and 56 and above each.

For the educational qualification, the lowest level of education is class 5 and the highest is graduate. The chart in fig-3 shows the comparison of the education level of the cattle farmers.

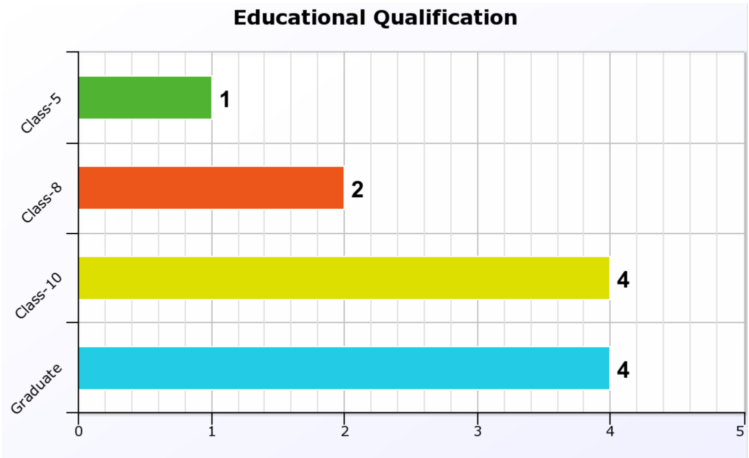


Figure 7.3: Educational Qualification of the participants

There is only 1 respondent who has studied up to class 5, 2 farmers up to class 8, 4 have studied up to class 10 equivalent of Secondary School Certificate (SSC). And, 4 of the cattle farmers are graduates. Therefore, as for the survey demography is concerned, our survey respondents are not educationally ignorant by any means.

Although sharing the contact number is optional, all of our respondents have shared their contact number with us which suggests their openness and supportive gesture towards any technological work in this field. About the smartphones they use, all of them are android smartphones with a minimum of 4GB RAM and 32GB ROM whereas, most of them are equipped with 4GB RAM and 64 GB ROM. The bar chart in Fig1 shows the RAM (Random Access Memory) and ROM (Read Only Memory) configuration of their smartphone.

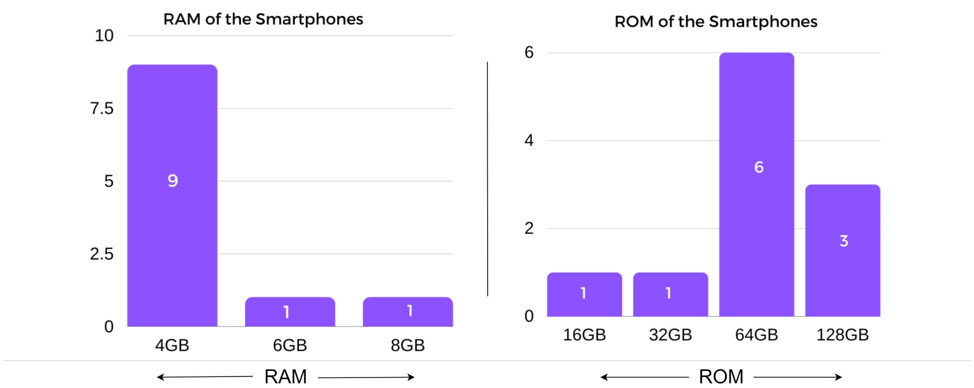


Figure 7.4: RAM, ROM of the smartphones

The smartphone data of our respondents is crucial to know from a technical point of view for running the application smoothly. All these demographic questions allow us to know our survey respondents better and determine the correlation between different responses.

7.3 Descriptive Analysis

The average age of the respondents is 45 years old. The maximum age is 78 whereas, the minimum age is 27 years old. As of the number of cattles in the farm, the total number of cattles combining the 11 cattle farms is 353. Therefore, according to the survey, every cattle farmer has an average of 32 cattles. And, the average price of their smartphone is BDT19000 to BDT20000.
The next part of the questionnaire is mainly about the user experience and thoughts about the 'CattleSavior' application after being used for seven days. Survey result of 5 point likert scale questions is in the table 6.1.
From the Table 6.1, the frequency of the cattle farmer using the 'Cattle Savior' app is 3.90 that indicates they often use the app. The average in terms of the smooth running of the application on their mobile device is 4.72 which means they strongly agree that navigating through the app is smooth and there are no bugs, crashes or any other issues. The users also strongly agree with the accurate detection of the diseases which has a mean value of 4.63. Then, the cattle farmers also agree about the economic loss that the app can reduce. Besides, they also agree that all the information provided by this application is important and relevant. Further, the users also acknowledge that they have learnt more about different diseases by using the application. Furthermore, with an average of 4.72, it is very likely for them to recommend the 'CattleSavior' application to other cattle farmers they come across. Moreover, the tiny value of the standard deviation indicates similarities in the responses. In terms of the 8 different features and the overall rating of the app, the user's review is given in the table 6.2.
From this table 6.2, we get a clear idea about what the user thinks about different features of the application. Besides, the low value of the standard deviation refers to the similar choices of different participants. Moreover, the overall rating of the application is 4.09 which indicates the user satisfaction. The bar chart in the fig-2 also shows the user rating of different features and the overall rating of the application.

7.4 Text Analysis

There are also 2 open-ended questions about the application. For suggesting any improvement of the existing features, participant-3 suggests adding more diseases in the disease detection feature. Participant-5 is very excited about all the features and suggests adding other livestocks such as goats, chicken, fish etc. Participant-9 from Savar suggests adding different information about feeding, managing different challenges during the pregnancy period of a cow, and specialized housing for different breeds of cattle. Also, participant-6 suggests adding more information about the reproduction of cows. Another open-ended question is about the necessity of any other feature. Most of the farmers are content with all the existing features. In response to this question, participant-1 from Uttara, feels the necessity of more features like the existing features but does not mention any.

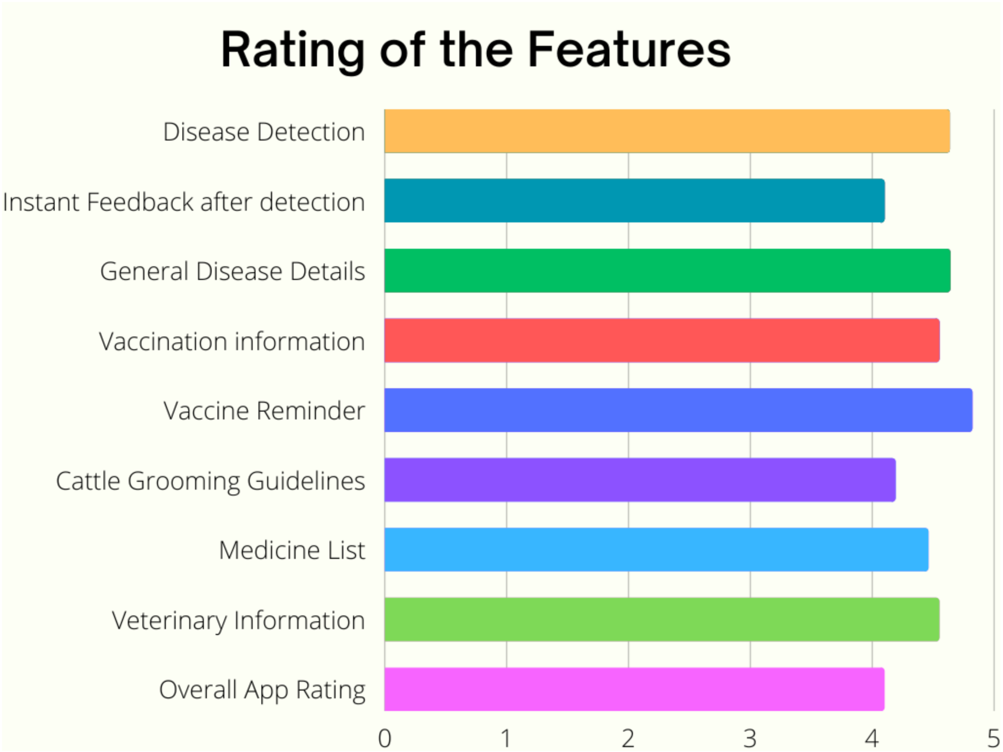


Figure 7.5: Rating of the features

Table 7.1: Survey result of 5 point likert scale questions

Questions	Average likert scale	Result	Standard Deviation
How frequently do you use the 'CattleSavior' app?	3.9	Often	1.22
Does the application run smoothly on your device?	4.72	Strongly Agree	0.47
Do you agree this application can detect diseases accurately?	4.63	Strongly Agree	0.67
Do you agree this application can reduce the economic loss caused by some cattle diseases?	4.45	Agree	0.52
Do you agree all the information provided by the application is important?	4.45	Agree	0.69
Have you learnt more about the diseases by using the app?	4.18	Agree	0.75
How likely are you to recommend this app to other cattle farmers?	4.72	Very likely	0.65

Table 7.2: the user's review in all features

Features	Average Likert scale	Result	Standard Deviation
1. Disease Detection	4.63	Very Good	0.5
2. Instant Feedback after detection	4.09	Good	0.7
3. General Disease Details	4.63	Very Good	0.5
4. Vaccination information	4.54	Very Good	0.52
5. Vaccine Reminder	4.81	Very Good	0.4
6. Cattle Grooming Guidelines	4.18	Good	0.6
7. Medicine List	4.45	Good	0.69

This final survey shows the successful implementation of our thesis plan which is initially generated from the first baseline survey. Different features of the mobile application serve well and enough for the cattle farmers of our country. Moreover, all the responses of the cattle farmers indicates the effectiveness of the overall work. Therefore, from the survey result, we can come to a conclusion that the cattle farmers are very positive about the 'Cattle Savior' application.

Chapter 8

Discussion

8.1 HCI

From the very beginning of our thesis work, our main priority has been to create an impact for the rural indigenous people of our country. Their life is mainly dependent on agriculture and unfortunately this sector is deprived of frequent modern technological improvement. Livestock is an integral part of our agriculture and cattle farming is the leader in this industry. Our work is based on the cattle diseases that occur frequently. Making the cattle farmer aware of different diseases, their treatments and preventions is necessary to minimize the economical loss they face. From the first survey, we know that for different types of external diseases of cattle the cost is most of the time more than BDT4000 which is not a small amount at all. In this era, smartphones have reached into the hands of all classes of people. So, we thought of developing a mobile application to make the life easier for the cattle farmers. In order to know about the cattle farmers, their needs and current situation, the first survey was conducted. Interestingly, we find almost all the cattle farmers using a smartphone. Besides, we get very positive responses from the cattle farmers which encourages us a lot. Participant-3 from Savar said, "This is a very good initiative. Best of luck." Also from the same area, participant-2 states, "If it is properly done, then it will be very helpful specially for the new cattle farmers. They will be very benefited financially as well." Participant-1 says, "It will be very helpful for those who are able to use smartphones." Besides, almost all the farmers in the survey response are very excited about using our application. We get a mixed response when asked if they are willing to pay for such a mobile application. Participant-9 from Uttara responded by saying, "It is better to call a doctor than relying on a smartphone. We do not think about money when any of our cattles get affected." On the other hand, participant-4 states, "If we can get the same treatment as the doctor provides from a mobile application, then of course, we are willing to pay. But it has to be reliable." About the diseases, most of them emphasize on the lumpy skin disease. They are very concerned with this as there are no appropriate vaccines as of yet for this disease. Foot and mouth is another very common disease that they face frequently. Also about the cattle eye disease, IBK which is commonly known as Pinkeye, some of the farmers face every year. As these diseases are mainly contagious, if not proper steps are taken immediately, it can become very deadly for a farm. Therefore, from the first survey, we become confident and feel encouraged to develop a mobile application.

After developing the mobile application, we get back to the same respondents from the first survey. This time we show them our application and install it on their smartphones for test use. All of them are very excited to run the application on their smartphone. We give them a full demonstrational overview of how all the features work. And, all of them agree that the application is very easy to navigate and understand. After 7 days of testing, we conduct our second and final survey focusing on the user experience of the application. According to the final survey on the 'Cattle savior' application, the 11 users gave an average rating of 4.09 out of 5 which shows the user satisfaction completely. In terms of improving the existing features, most of the users do not feel the importance of any kind of correction or improvement in the existing features. Participant-4 from Uttara, who is a former teacher and has been running a cattle farm of 150 cattles with almost 30 years of experience in this area states, "All the information and features you provided is enough. I do not feel the necessity of including any more information. All of you have done a great job." He is also very excited about the application and rated the application 5 out of 5. Participant-2 from the same area is also very supportive towards us and told us that every single feature and information on the application is very important and not irrelevant by any means. On the flip side of the coin, participant-9 from Savar, is very offish towards the application. He thinks that this application cannot make any difference for the cattle farmers. He rated the application 2 out 5. Among the 11 different responses, 10 of them are positive. Therefore, by the calculation, the user satisfaction rate is 90.9%. So, we can say that the main objective of creating the 'Cattle Savior' application and having an impact on the cattle farmers life is successfully achieved.

8.2 Deep Learning

At first, we collect datasets for LSD, FMD and IBK from different places, then we start different deep learning experiments on those datasets. For the deep learning model, we have tried to build custom CNN architectures. From our custom CNN architecture, we get a good performance. After that, we have tried other related pre-trained CNN models such as VGG-19, InceptionresV2, Resnet50 and so on. Moreover, we have also tried ViT (Vision Transformers). Since our dataset was very small, ViT did not perform as well as we know that ViT only performs well on large datasets. So, we have tried all the possible ways to compare and get the best possible model. By comparing all these models, we can clearly see that our custom CNN models perform better than other pre-trained models and our custom CNN model is also a light weight model as well. We need a very light weight and good performance model, since we want to take our model in our CattleSavior app. For this reason, we convert our TF model into TFlite model which becomes lighter weight from the previous TF model and this TFlite model performs really well in mobile applications.

Chapter 9

Limitation and Future Work

9.1 Limitation

By the time we finish our work in this sector, we come across some challenges and limitations. The main limitation is the lack of data. In order to collect the diseased image data for detecting different diseases, we discuss with some veterinarians and IT technicians of different veterinary hospitals. But, they cannot suggest any right place to look for the data let alone provide the data by themselves. Moreover, building a completely new dataset is very difficult and time consuming. So, as it turns out there is hardly any other way but to work with the existing dataset alone which is very minimal. Therefore, for any machine learning or deep learning based project or thesis which require any kind of medical data of the livestock industry, dataset is the main concern. Besides, we also face some challenges to develop the mobile application in Flutter. This multi-platform application building tool is not fully stable yet. Also, it is continuously evolving and having version updates. As a result, handling different types of errors is tiresome and frustrating. Besides, the flutter community is very small. So, it is hard to find solutions or suggestions regarding any problem.

9.2 Future Work

This sector has a lot of potential to showcase different aspects of Artificial Intelligence and IOT to improve the overall agricultural of a developing country like Bangladesh. We plan to continue our deep learning based work in this sector and improve further. As we have already approached collecting datasets for different diseases of cattle, our plan is to add more diseases for detection into the 'Cattle Savior' application. Besides, we have plans to add some other features into the application as well. One feature that we like to add is 'Find the Nearest Veterinary Hospital'. By this feature, cattle farmers can be able to locate the nearest veterinary hospital according to their own location. They also can see the fastest route to reach the hospital which will also show the estimated time. This feature may come in handy at times of any emergency. Another feature that we have a clear vision about is 'Cattle Community'. We like to establish an online community of cattle farmers where they can interact with each other by sharing their thoughts, ideas, problems, experience, solutions and so on. Veterinarians are also welcomed in this community to help and guide the cattle farmers. This feature can become a breakthrough in information sharing for the cattle farmers. In addition to developing these features, monitoring the ‘Cattle Savior’ application and keeping all the data up to date is also in our priority list.

Chapter 10

Conclusion

Different external diseases of cattle can become life-threatening if they are not detected along with the necessary treatment on time. Also it can create an economic loss for the cattle farmers, which will eventually affect the overall growth of the country. This study includes three of the most common external diseases faced by Bangladeshi cattle farmers which is determined through a survey conducted on 26 cattle farmers across 3 different locations of the country. The paper reflects the whole process of detecting Lumpy Skin Disease, Foot and Mouth Disease, and Infectious Bovine Keratoconjunctivitis using the Deep Learning model and then implementing it on a mobile application titled 'Cattle Savior'. Moreover, it provides the farmer with modern suggestions as well as some preventive measures through the application with some necessary features that can become really convenient for the cattle farmers of the country. However, we have to build lightweight applications so that our cattle farmers can easily use it in their low-end devices as well. Here in this study, we have explored many deep learning models(custom CNN model and different pre-trained models). Among them, we get 97.62% test accuracy achieved by our custom CNN model and it is also a very lightweight model. We reduce the size of this model even more lightly by converting this tensorflow model to a tensorflow lite model and storing it in our Android studio. After that, we built all the required features by using Flutter. Finally, the application can detect the three different diseases while also providing the necessary feedback and suggestions along with six other helpful features for cattle farmers. Moreover, eventually, through the final survey, the successful implementation of the study is also measured.

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