# Identify Animal lumpy Skin Disease Using Image Processing and Machine Learning

**A Thesis Presented**

**by**

**Elias Girma**

**to**

**The Faculty of Informatics**

**of**

**St. Mary's University**

**In Partial Fulfillment of the Requirements for the Degree of Master of Science**

**in**

**Computer Science**

**July, 2021**

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# ACCEPTANCE

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**Thesis Examination Committee:**

| | | |
|---|---|---|
| **Internal Examiner** | **Signature** | **Date** |
| **External Examiner** | **Signature** | **Date** |
| **Dean, Faculty of Informatics** | **Signature** | **Date** |

**July, 2021**

## DECLARATION

I, the undersigned, declare that this thesis work is my original work, has not been presented for a degree in this or any other universities, and all sources of materials used for the thesis work have been duly acknowledged.

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This thesis has been submitted for examination with my approval as advisor.

______________________________________________

Full Name of Advisor

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**July, 202**

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Finally, my grateful thanks go to Oromia region Bale zone Medawelabu wereda and Arsi zone Chole wereda Livestock production offices staffs, for their kind cooperation through data collection process.

Elias Girma

# Abstract

Ethiopia has the largest livestock population in Africa. However, productivity of the sector in Ethiopia has multifaceted constraints; the Lumpy Skin Disease is one of the major factors. Lumpy Skin Disease is known as a major risk to cattle production and substantial impacts on livelihoods and food security especially for our country. Currently, detection of Lumpy Skin Disease in our country is assessed manually. However, manual evaluation takes significant amount of time and requires trained professional and experienced person. Therefore, technology is needed to prevent animal disease epidemics. Automated detection of Animal Lumpy Skin Disease has advantages over the manual technique. Detection of Lumpy Skin Disease in Cows is developed in literature. But Animal Lumpy skin disease has different classification based on its severity. There is a need to further identify the different stages of Lumpy skin disease to know to what extent the animal is affected by lumpy skin disease. In this study, Lumpy skin disease detection model is constructed using Convolutional Neural Network (CNN) for feature extraction and SVM for classification. CNN is the state of the art for deep feature extraction, hence we used it for feature extraction. The model used to detect and classify animal Lumpy Skin Disease skin diseases into Severe, Mild and Normal. The dataset is collected from Oromia region Bale zone Medawelabu wereda and Arsi zone Chole wereda Livestock production offices and from internet external images repository. After collecting data, Image augmentation, Image Preprocessing, and Image Segmentation techniques are applied to enhance image quality and identify region of interest. During image preprocessing, the image is resized to 200x200. Gaussian filtering is applied to remove noise and Histogram equalization to balance the intensity of image. Adaptive thresholding segmentation method is used to identify region of interest. Out of the total 1740 image dataset, 80% is used for training and 20% for testing.

Experimental results show that, SVM classifier outperforms RF(Random Forest) and Softmax classifiers. Quantitatively, an overall accuracy of 95.7% is achieved by using SVM classifier; on the other hand, RF achieves 87. 4% and Softmax classifier achieves accuracy 94.8%.

Noises in the image is a challenging task for properly detecting the region of interest and hence we recommend as a way forward to use advanced noise removal techniques to improve image quality for proper segmentation and Lumpy skin disease detection.


**Keywords:** Animal Lumpy Skin Disease, convolutional neural network, Random Forest, Image Processing

Contents

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# List of Abbreviations

| | |
|---|---|
| CNN | Convolution Neural Network |
| DIP | Digital Image Processing |
| DSLR | Digital Single Lens Reflex |
| EVF | Electronic View Finder |
| GDP | Grose and Development Plan |
| k-NN | K-Nearest Neighbors |
| OIE | Organization for Animal Health |
| PPEG | Joint Photographer Expert Group |
| RF | Random forest |
| RGB | Red, Green, Blue |
| SVM | Support Vector Machine |
| SLR | Single-Lens Reflex |
| LoG | Laplacian of Gaussian |

# CHAPTER ONE

# INTRODUCTION

## 2.1 Background

Ethiopia has the largest livestock population in Africa. The livestock population is estimated to be 65.35 million cattle, 39.89 million Sheep, 50.50 million for goat, 2.11 million horses, 8.98 million donkeys,0.38 million mules, and about 7.70 million camels in the country[107], which shows that there is a great potential to export substantial numbers of live animals and their products. However, there are different types of animal skin diseases in Ethiopia. Because of these diseases, the country has not been able to get the benefits from animal production. The most common animal skin diseases in Ethiopia are Dermatophilosis, lumpy skin disease, pediculosis, acariasis, ked, sheep and goat pox [2]. Due to the prevalence of highly contagious transboundary animal diseases such as lumpy skin disease, the full potential of sub-sectors has not been realized in Ethiopia [1].

Lumpy Skin Disease is one of the serious animal skin disease and caused by lumpy skin disease virus. The Animal Lumpy Skin Disease is characterized by fever, enlarged lymph nodes, firm and circumscribed nodules in the skin and nodules are particularly noticeable in the hairless areas. Lumpy skin disease is currently endemic in most countries. It is animal viral diseases which cause several economic problems including significant milk yield loss, infertility, abortion, trade limitation and sometimes death in most African countries including Ethiopia [3]. Lumpy Skin Disease virus is transmitted from infected to non-infected animals through direct contact by mosquitoes, flies, and ticks. The disease can also be spread through contaminated feed, water, and equipment. The virus is not transmissible to humans [4].

Clinical sign of Lumpy Skin Disease is Skin nodules with 5-50 mm size rising above the skin [5]. The nodules can cover the entire body or only few can appear. The nodules can disappear or ulcerate leaving scars. The clinical diagnosis is confirmed by laboratory testing of blood samples and tissue samples from the skin lesions [5]. To suspect Lumpy Skin Disease there is no commercial diagnostic test kits but usually based on the characteristic observed as clinical signs, differential diagnosis, and confirmation is done by laboratory tests. Lumpy Skin Disease should be detected clinically when there are characteristic skin nodules, fever and enlargement of superficial lymph nodes [6]. Ethiopia specially in remote area early detection of Lumpy Skin Disease is most important to avoid the transition of the disease to other animals. So, this research attempts to design automatic animal lumpy skin disease detection using image processing methods.

## 2.2 Motivation

Ethiopia has the most abundant livestock population in Africa. The livestock production plays an important role in the economies. However, these livestock do relatively well under the traditional production system. Technology needs to improve traditional production system, especially in the animal medical field. One of the main branches of veterinary medicine that deal with the skin, nails, hair and its diseases is called Dermatology. There are a numbers researches conducted towards human skin diseases detection using image processing and machine learning techniques [44]. But animal skins different from human skins for a number of reasons, such as the fact that animal skins are thick and hairy, so special studies are needed. Research conducted on Detection of Lumpy Skin Disease in Cows [106]. But Animal Lumpy skin disease has different classification based on its severity. There is a need to further identify the different stages of Lumpy skin disease to know to what extent the animal is affected by lumpy skin disease.

Animal Lumpy skin disease detection based on severity stages using image processing is an untouched area. To reduce livestock mortality rate; due to skin diseases, early-stage detection is very important. The implementation of image processing technology in animal health industry has important function by increasing the efficiency of experts. So, the motivation of this work is to contribute towards the achievement of animal skin disease detection automatically in our country.

## 2.3 Statement of the Problem

Livestock sector in Ethiopia is composed of 65.35 million cattle, 39.89 million sheep, 50.50 million goats, 2.11 million horses, 8.98 million donkeys,0.38 million mules, and about 7.70 million camels and contribute 15 to 17 % of GDP and 35 to 49 % of agriculture GDP and 37 to 87 % of the household income [107, 1]. However, productivity of the sector in Ethiopia has multifaceted constraints; the Lumpy Skin Disease is one of the major factors [7]. According to World Organization for Animal Health (OIE), Lumpy Skin Disease is one of the most economically important viral diseases listed as notifiable trans-boundary animal diseases and the second significantly important cattle disease in Ethiopia [2]. Lumpy Skin Disease is known as a major risk to cattle production and substantial impacts on livelihoods and food security especially for our country.

In Ethiopia lumpy skin disease was first observed in southwest of Lake Tana in 1983 and spread almost all regions of the country [38]. From 2007 to 2011 a total of 1352 disease outbreaks of Lumpy Skin Disease have been documented and the highest outbreak was registered in Oromia region and the lowest in Afar region [3]. There is no specific antiviral treatment available for Lumpy Skin Disease infected. The annual loss due to mortality ranges from 8–10% for cattle, 12–14% for sheep, 11–13% for goats and 56.9% for poultry. These figures are much higher for calves, lambs and kids [45]. The direct and indirect losses from livestock disease have significant economic, food security and livelihood impact on livestock keepers and the national economy [4]. Affected animals showed clinical signs characterized by generalized skin nodules, enlarged peripheral lymph nodes and edema of the dependent parts [9]. Diagnosis of Lumpy Skin Disease is done based on characteristic of clinical signs. These may base on presence of fever, nodules on the skin, mucous membranes, enlargement of superficial lymph nodes and edema of the skin in livestock, but it is a likely diagnosis that must be confirmed by laboratory methods [10]. But there are only 17 regional veterinary laboratories throughout Ethiopia and they are not functioning at their full capacity [5]. According to [6], veterinary services in some urban area encounter a number of problems. Among these problems qualified veterinary staff, distance from the home of clients, lack of equipment’s, and laboratory materials. The national animal health service delivery in Ethiopia covers only 45% of the country’s population [12].

Currently, detection of Lumpy Skin Disease in our country is assessed manually. However, manual evaluation takes significant amount of time and requires trained professional and experienced person. This is especially evident during large scale inspection in the process of exporting. The animal health service delivery in Ethiopia has nowadays covers only 9% by veterinarians from the total 30% coverage [46]. Moreover, in our country there is no sufficient veterinarian and laboratories throughout the country. Therefore, technology is needed to prevent animal disease epidemics. Automated detection of Lumpy Skin Disease has advantages over the manual technique. The major advantage is it helps experts to describe visible attributes accurately. Hence, the use of automated image processing helps to eliminate the problems associated to detect Lumpy Skin Disease using manual evaluation. The speed of analysis is also much higher than any of the manual methods [11].

Currently, various researches have been done to automate detection of human skin disease by using machine learning and deep learning techniques. However, as to the researcher knowledge insufficient studies are conducted to detect animal skin disease using image processing and machine learning. Bezawit [47] applied image processing for classifying cattle skin disease using CNN model. Bezawit considered Lumpy skin disease, Ringworm and Wart skin diseases, in which Lumpy skin disease is taken as one class. Gaurav Rai, Naveen, Aquib Hussain, Amit Kumar, Rahul Nijhawan[106], A Deep Learning Approach to Detect Lumpy Skin Disease in Cows. But Animal Lumpy skin disease has different classification based on its stages. There is a need to further identify the different stages of Lumpy skin disease to know to what extent the animal is affected by lumpy skin disease. Because the effective control Lumpy skin disease in endemic and non-endemic areas requires rapid and accurate diagnostic methods to confirm a presumptive diagnosis [18]. It is therefore the aim of this study to apply image processing and machine learning for detecting the stages of lumpy skin disease in animals.

Therefore, in this research an attempt is made to explore and address the following research questions: -

- ✓ What are the suitable image processing techniques for segmenting the captured images?
- ✓ What is the suitable classification for Animal Lumpy Skin Disease detection?
- ✓ To what extent the proposed approach performs in detecting Animal Lumpy Skin Disease?

## 2.4 Objective of the study

### 2.4.1 General objective

The general objective of this research is to design an appropriate detection model which recognizes Lumpy animal skin disease using image processing techniques and machine learning algorithms.

### 2.4.2 Specific objectives

The specific objectives of this study are the following.

- To prepare Animal Lumpy Skin Disease image data set for experimentation
- To select suitable segmentation and detection of Animal Lumpy Skin Disease.
- To construct detection model that identify Animal Lumpy Skin Disease with high sensitivity.
- To evaluate the performance of the proposed Lumpy Skin Disease detection model.

## 2.5 Scope and Limitation of the Study

This research scope is limited to the development of a predictive model for Animal Lumpy Skin Disease detection using image processing and machine learning. Moreover, the study is limited to build a prototype for Lumpy Skin Disease prediction based on severity stages and use classification Machine learning technique. The classification algorithms selected by the researcher in this study to develop prediction models. Besides the promising findings observed in this study, the following major limitations are recorded:

- ✓ Because of lack of enough local images, the training dataset is collected from Google search engine and local images collected using mobile phone is used for testing.
- ✓ The study was lack of literatures related to image processing and data mining techniques to detect animal skin disease.
- ✓ The study only detects an input image into either of three different classes' i.e., Normal (uninfected skin with Lumpy Skin Disease) and Mild (infected skin with mild case Lumpy Skin Disease) and Severe (infected skin with severe case Lumpy Skin Disease).

## 2.6 Significance of the study

Lumpy Skin Disease is one of the major Trans boundary livestock diseases in Ethiopia. It is a major risk to cattle production and substantial impacts on livelihoods and food security especially for our country. Usual the Lumpy Skin Disease diagnosis is based on the characteristic clinical signs of the disease, and confirmation is done by laboratory tests. However, these diagnostic needs high cost of examinations and the lack of specialists prevent many livestock's from receiving effective treatment. Because of these challenges, developing lumpy animal skin disease detection prototype using image processing and machine learning becomes very important. This research work, helps to examine a large number of images in short time and reduces the cost and workload of Veterinaries specialists. The Significance of the study for researchers, are to add some input on the area that encloses applications of image processing and machine learning over animal health sector, and can also be a starting point for other researchers on sector of artificial intelligence.

## 2.7 Methodology

In this section, the methodology of the proposed system for detection of Lumpy Skin Disease is described. Methodology is the specific procedures or techniques used to identify, select, process, and analyze information about a topic [48]. In a research, the methodology specifies the step-by-step procedure followed and methods used for solving the problem and achieve its objective. So, this research work is carried out under the following methods and procedures.

### 2.7.1 Research design

Experimental research is one of the most widely used approaches for Image processing and machine learning. An experiment Research is manipulating one or more independent variables manipulated by the researcher and measure their effect on one or more dependent variables [49]. There are three major processes involved in experimental research. First, the required data is captured and then processed to make it ready for experimentation. This is followed by tools and methods selection for implementation. Finally, the implemented system is evaluated using test data set. So, the research follows experimental research in order to implement a prototype for animal Lumpy skin disease detection.

### 2.7.2 Data Collection

Image dataset used to address the objective of this study. A number of image data is required for the model to be trained as well to be tested. For training the image data can be collected from different veterinary clinics and images that are found on the Internet. We collected 250 Lumpy Skin Disease images from Internet and Oromia region Bale zone Medawelabu wereda and Arsi zone Chole wereda Livestock production offices. The images were collected by using a digital camera in certain conditions. For testing images acquired with smart phone camera with 18 mega pixel and be ready for the dataset preparation.

### 2.7.3 Dataset Preparation

Datasets can be prepared using the images that are collected from different veterinary clinics and images that are found on the Internet. In this research work images that are collected form internet dataset are to be used for model training and images that are collected from local veterinary clinic used for testing purposes, in which these animal skin image files differentiated between healthy and infected categories manually at first and speared infected categories into Severe and mild case. The dataset prepared based on 80% of the dataset is used for training and the rest 20% of the dataset is used for testing the model.

### 2.7.4 Implementation Tool

For this research to detect Animal Lumpy Skin Disease, we use several open-source libraries. We used Anaconda environment and Python programming language for scientific computing. Python programming language were used for preprocessing, feature extraction and classification. Because, python’s simplicity, readability, and compatibility wide range of third-party libraries available that is tailored for the use in the deep learning process.

We also installed and used python libraries like TensorFlow, Keras, OpenCV, and Matplotlib. TensorFlow library is used for scientific computing tenders such as neural networks. Keras is user-friendly and runs on top of TensorFlow. It supports modularity and it is easily extensible and easy to use. We have used Jupiter Notebook tools to perform the experiment. The experimentation was conducted using a Computer with Processor; Intel(R) Core(TM) i5-10210U CPU @ 1.60GHz, 2112 Mhz, 4 Core(s), 8 Logical Processor(s).

### 2.7.5 Evaluation methods

To evaluate the performance of the protype we used different measures such as Accuracy, Recall, Precision and F-score. These metrics are based on the number of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) samples.

### 2.7.6 Organization of the Thesis

This research work is organized into the following five chapters. Chapter one includes the background of the study, Motivation, statement of the problem, objective of the study, the scope and limitation, Significance of the study and research methodology. Chapter two reviews concepts and methods relevant and related to the proposed approach. Chapter three detailed description of the proposed methods and algorithms is discussed. Preprocessing, segmentation, feature extraction and classification are described in detail. Chapter four implementation and experimental results are presented. Finally, in chapter five provides conclusion and recommendation for scholars interested in the area.

# CHAPTER TWO

# LITERATURE REVIEW

## 3.1 Overview

Lumpy Skin Disease is an acute to chronic viral disease characterized by skin nodules in the skin and relevant diagnosis procedures are required for early detection of these virus. The involvement of image processing has a potential to reduce the workload in a typical determiners and regional lab and improve the quality of the interpretation. This chapter gives an overview of the structure and function of the skin, Lumpy skin disease, Clinical signs and postmortem lesion and treatments. In the last Section, related works review that summarizes state of the art detection methodologies that are in published in the skin disease detection using image processing methods research area.

## 3.2 Structure and function of the skin

The skin is also known as the integumentary system and the largest organ of the body and protects animals from external influences. It has a complex structure, being composed of many different tissues [14]. It also protects the animal body from physical damage and bacterial invasion. The primary morphological function of the hide or skin of animal is to allow for thermo-regulation, gaseous exchange, protection and provide cover.

The skin has an array of sense organs, which sense the external environment [14]. It is one of the first systems affected when an animal becomes sick. It is important for anyone working with animals to have knowledge of the structure and functioning of the skin. Animal skins generally consist of three layers: Epidermis, Dermis and Hypodermis [14].

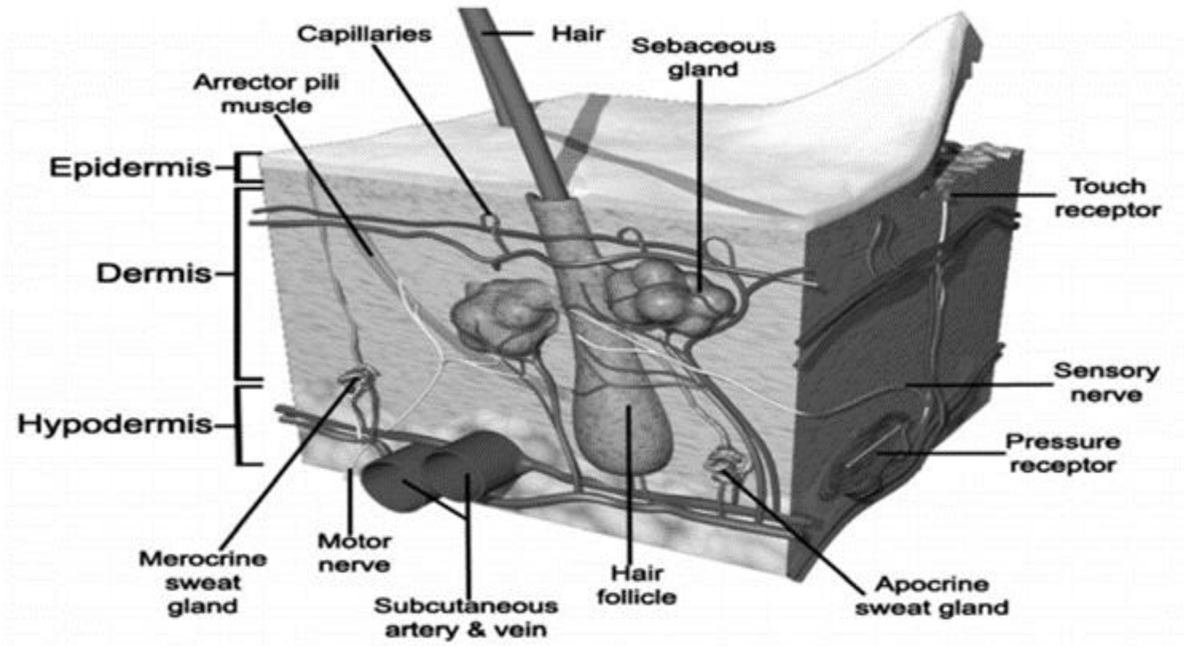



*Figure 3-1   Structure of skin [14]*

### 3.2.1 Epidermis

Epidermis is the outermost layer of the skin. It is the superficial epithelial layer and covers 1-2% of the total thickness of the entire hide. The epidermis is 50-150 μm thick, depending on the part of the body and skin type [14]. It prevents water loss, is a barrier against toxic substances, withstands mechanical stress and is involved in immune responses. The epidermis is composed of multiple types of cells, including keratinocytes, melanocytes, Langerhans cells, and Merkel cells [101]. Each of these cells has special functions.

Keratinocytes are found in the outermost layer of the skin, called the epidermis. The epidermis is composed of 95% keratinocyte cells [52]. Keratinocytes provide a protective layer that is constantly being renewed in a process called keratinization. In this process, new skin cells are created near the base of the epidermis and migrate upwards. This produces a compact layer of dead cells on the skin surface. This layer keeps in fluids, salts, and nutrients, while keeping out infectious or noxious agents.

Melanocytes are located at the base of the epidermis, the outer root sheath of hairs, and the ducts of the oil and sweat glands. The melanocytes produce the skin and hair coloring (pigment) called melanin. Production of melanin is controlled by both hormones and the genes received from parents. Melanin helps protect the cells from the damaging rays of the sun [19].

### 3.2.2 Dermis

The dermis, also known as “true skin”, is thick than the epidermis and composed of collagen rich connective tissue that contains fibroblast cells that produce collagen and elastin, which are responsible for the pliability and strength of skin. [14] This layer provides mechanical support and feeds the epidermis and skin appendages. The blood vessels that supply the epidermis with nutrients are located in the dermis. Blood vessels also regulate skin and body temperature. Sensory nerves are located in the dermis and hair follicles. Motor nerves are also present. The skin responds to the sensations of touch, pain, itch, heat, and cold. The dermis secretes the protein collagen, which supports the skin. There are also immune cells in the dermis that defend against infectious agents that pass through the epidermis.

### 3.2.3 Hypodermis

The hypodermis is found below the dermis. It is also known as subcutaneous tissue or adipose panniculus. The hypodermis is mostly constituted by adipocytes surrounded by loose connective tissue. The thickness of this layer is variable depending on the body part, the age and it is also different between men and women. Head lacks hypodermis and the dermis is in contact with the cranial bones. Smooth muscle cells for hair to stand erect can sometimes be found in the hypodermis, and a few striated muscle cells in the neck and face.

## 3.3 Lumpy skin disease and its Clinical signs

The incidence of Lumpy Skin Disease is high during wet seasons when populations of the flies are abundant. It is one of the most main viral diseases of cattle, causing loss of condition in infected animals and permanent damage to hides [19]. The Lumpy Skin Disease incidence decreases or ceases during the dry season. Lumpy Skin Disease Virus transmission occurs mainly via insect Vectors. It causes high significant economic losses as a result of reduced milk production, abortion, infertility, weight loss and decreased skin [24, 20].

Lumpy Skin Disease is a disease affecting cattle and characterized by fever, enlarged lymph nodes, firm, circumscribed nodules in the skin and ulcerative lesions particularly of the mucous membrane of the mouth [18].

Fever is the initial sign of Lumpy Skin Disease. The disease is characterized by large skin nodules covering all parts of the body, fever, enlarged lymph nodes reduction in milk production, some depression and reluctance to move nasal discharge and lachrymation [21]. The clinical signs of Lumpy Skin Disease depend on the host immunity status, age, sex and breed type. Typically, younger animals are usually affecting and show more severe disease than adult ones [3,26]. Lumpy skin disease may be occurred acute, sub-acute and chronic form. The nodules developed on skin are vary from 2 cm to 7 cm in diameter, appearing as round, well circumscribed areas of erect hair, firm and slightly raised from the surrounding skin and particularly conspicuous in short-haired animals. In long-haired cattle the nodules are often only recognized when the skin is palpated or moistened. In most cases the nodules are particularly noticeable in the hairless areas of perineum, udder, inner ear, muzzle, eyelids and on the vulva [3, 26].

## 3.4 Diagnosis

The diagnosis of Animal Lumpy Skin Disease is usually based on the characteristic clinical signs of the disease, and confirmation is done by laboratory tests using molecular techniques of conventional or real time polymerase chain reaction (PCR) and cell culturing [28, 22]. Rapid diagnostic confirmation is fundamental for the successful control and eradication of Lumpy Skin Disease in endemic and particularly in non-endemic countries [3].

## 3.5 Overview of Digital Image Processing

In computer science, digital image processing is the use of a digital computer to perform some operations on a digital image, in order to get an enhanced image or to extract some useful information from it. Since images are defined as a two-dimensional function, the mathematical function f(x, y) where x and y are the two co-ordinates horizontally and vertically. Note that, a digital image is composed of a finite number of elements, each of which has a particular location and value. Pixel is the term used most widely to denote the elements of a digital image. The value of f(x, y) at any point is gives the pixel value at that point of an image [31, 32].

Computer vision seeks to develop techniques to help computers to understand the content of digital images. It is applied in marketing, agriculture, healthcare, and other industries. The main tasks in a computer vision are to locate and recognize the objects within an image, since one image may contain a number of objects in it. For a human being, by looking the image of the objects, they can easily understand the object and what's inside. But the main question is how to teach this to a computer to understand the objects and what's inside. An image is just a collection of pixels used to visual representation of something. It is hard for the computer vision to understand images in to understand what changes in pixels and what changes the object. Handling even a simple machine with a simple interpretation and recognition takes a great deal of skill and mathematics [53]. As shown in figure 2.2, digital image processing can be divided into three classes: Low Level, mid- Level, and high-level processes.

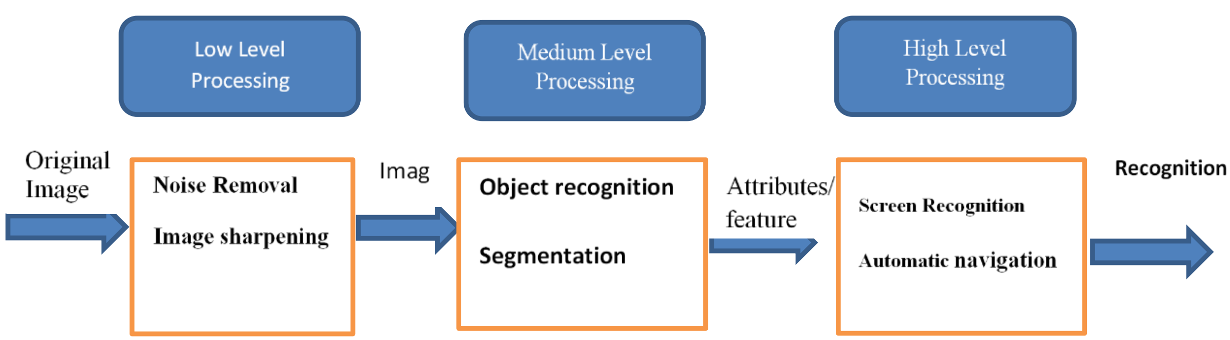



*Figure 3-2 Levels of Image processing[29]*

No imaging system gives images of perfect quality. Hence, there is a need to apply low level processing, such as image enhancement, image restoration. In image enhancement the aim is to manipulate an image in order to improve its quality than original image for specific application. That includes reduce noise, contrast enhancement, and image sharpening. The middle level of image processing is mainly concerned with extracting descriptions of the scene from the image descriptions extracted at the low level. High-level Processing deals with the automatic extraction of information from an image or sequence of images. It is also an essential part of computer vision systems. Image analysis usually returns numeric values and/or graphical information about the image characteristics that are suited for classification, defect detection, or prediction of some of the quality properties of the imaged object [23, 37].

## 3.6 Fundamental Steps of Digital Image Processing

Different image processing applications may follow different steps. However, there are some fundamental steps that every image processing application passes through.

### 3.6.1 Image Acquisition

The first stage in automating image analysis system is image acquisition, which gives an idea regarding the origin of digital images. It consists of scanners, digital camera, cell phone camera or web camera that acquire the pictures. However, if the image has not been acquired satisfactorily then the intended objective may not be achievable. Image can also be acquired from satellite and medical imaging equipment like X-Ray machine, MRI machine for medical diagnosis applications, like tumor detection and cancer detection [24].

We use different cameras for different use. For x-ray image, we use a camera that is sensitive to x-ray. For infra-red image, we use camera which are sensitive to infrared radiation. For normal images we use cameras which are sensitive to visual spectrum [54]. Digital cameras are mainly classified according to their use, automatic and manual focus. Here are the classifications. Figure 2.3 – 2.8 shows the different types of analog and digital camera that are available for use on the market.

### A. Compact digital cameras

Compact cameras are the most widely used and the simplest cameras to be ever seen. They are used for ordinary purposes and are thus called “point and shoot cameras”. They are very small in size and are hence portable. Since they are cheaper than the other cameras, they also contain fewer features, thus lessening the picture quality [55].


*Figure 3-3 Compact digital cameras [55]*

### B. Bridge cameras

Bridge cameras are most often mistaken for single-lens reflex cameras (SLR). They have the same characteristics their features are different. Some of its features are: Fixed lens, Small image sensors, Auto-focus using contrast-detect method and also manual focus, Image stabilization method to reduce sensitivity.


*Figure 3-4 Bridge Cameras [55]*

### C. Digital single lens reflex cameras (DSLR)

This is one of the most high-end cameras obtainable for a decent price. They use the single-lens reflex method just like an ordinary camera with a digital image sensor. The SLR method consists of a mirror which reflects the light passing through the lens with the help of a separate optical viewfinder.


*Figure 3-5 Bridge Cameras [55]*

D. **Electronic viewfinder (EVF)**

This is just a combination of very large sensors and also interchangeable lenses. The preview is made using an EVF. There is no complication in mechanism like a DSLR.

*Figure 3-6 Electronic View Finder [55]*

E. **Digital rangefinders**

This is a special film camera equipped with a rangefinder. With this type of a camera distant photography is possible. Though other cameras can be used to take distant photos, they do not use the rangefinder technique.

*Figure 3-7 Digital rangefinders [55]*

F. **Line-scan cameras**

This type of cameras is used for capturing high image resolutions at a very high speed. To make this mechanism possible, a single pixel of image sensors is used instead of a matrix system. A stream of pictures of constantly moving materials can be taken with this camera. The data produced by a line-scan camera is 1-dimensional. It has to be processed in a computer to make it 2-D. This 2-D data is further processed to obtain our needs.

*Figure 3-8 Line-scan cameras [55]*

### 3.6.2 Image Preprocessing

Preprocessing is technique which is applied for the enhancement of an image in processing the images. It used to prepare images for further analysis, including interest point and feature extraction. Most image-processing techniques involve removing low-frequency background noise, normalizing the intensity of the individual particle's images, removing reflections, and masking portions of images [13]. It is an essential step in image processing in order to remove noise of the images and enhance the quality of original image. Good selection of preprocessing techniques can greatly improve the accuracy of the system. The objective of the preprocessing stage can be achieved through three process stages of image enhancement, image restoration and noise removal [25].

#### A. Image enhancement

It is the process of filtering image (removing noise, increasing contrast, etc.) to improve the quality. There are many enhancement techniques that can be applied to an image. The enhancement methods can broadly be divided in to the following two categories [2.1]: Spatial domain techniques and Frequency domain techniques.

Spatial domain techniques directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. An image processing operator in the spatial domain may be expressed as a mathematical function T [.] applied on f(x, y) to produce a new image g(x, y). T can operate on a set of input images, such as performing the pixel-by-pixel sum of K images for noise reduction as follows [33,34]:

$g(x, y)=T[f(x, y)]$ ………………………………………………*Equation 3-1*

In frequency domain methods, the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. The new image g(x, y) is formed by the convolution of an image f(x, y) and a linear position invariant operator h(x, y) [33, 34].

$g(x, y)=h(x, y)*f(x, y)$ ……………………………..*Equation 3-2*

**B. Image Restoration**

It is the process of improving appearance (reducing blurring) of an image by mathematical or probabilistic models. In image restoration is the operation of recovering an image from a degraded version of it. The concerns of the image restoration are the removal or reduction of degradations which are included during the acquisition of images; for example, noise, pixel value errors, out of focus blurring or camera motion blurring using prior knowledge of the degradation phenomenon. Input image is degraded by a degradation function, say h(x, y) and channel transmission noise n(x, y), degraded image g(x, y) can be obtained. In image restoration the target is to obtain the approximate target to the input. The blurred image can be described with the following equation [35].

$$g(x, y) = h(x, y) * f(x, y) + n(x, y) \quad \text{Equation 3-3}$$

### 3.6.3 Image Segmentation

Image Segmentation is the process of partitioning the image into multiple segments to regions of similar attributes. It typically used to locate objects and boundaries in images. It is one of the most difficult tasks in DIP. Segmentation plays an important role in image processing since separation of a large image into several parts makes further processing simpler.[27] The segmentation process is based on various information found like color information, boundaries or segment of an image. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. The main objective of segmentation is to reduce the information and to making easy analysis possible. [13] Several image segmentation techniques are exist, which partition the image into several parts based on certain image features like pixel intensity value, color, texture, etc. [27]. However, popular techniques in image segmentation are: segmentation by thresholding, segmentation by edge-based method and region-based segmentation.

### A. Segmentation by Thresholding

Threshold segmentation is the simplest method of image segmentation and also one of the most common parallel segmentation methods [42]. It is the operation of converting a multi-level image into a binary image. It involves the basic assumption that the objects and the background in the digital image have distinct gray level distributions. The image is converted into binary image based on whether the image pixels fall below or above the threshold value. The purpose of thresholding is to extract those pixels from some image which represent an object. Though the information is binary the pixels represent a range of intensities [41, 39, 46]. Threshold segmentation can be divided into local threshold method and global threshold method [42].

The global threshold method divides the image into two regions of the object and the background by a single threshold [42]. The intensity value of the input image should have two peak values which correspond to the signals from background and objects. It tells the degree of intensity separation between two peaks in an image [56]. Global thresholding, using an appropriate threshold T: Suppose that a gray-level image f can take K possible gray levels, 0, 1, 2, . . . , K–1, define an integer threshold, T, that lies in the gray-scale range of T, (0, 1, 2, . . . , K-1). The process of thresholding is a process of simple comparison: each pixel value in f is compared to threshold, T. Based on this comparison; a binary decision is made that defines the value of the corresponding pixel in an output binary image [47,48].

If g(x, y) is a thresholded version of f(x, y) at some global threshold T, pixel value of the grey scale image is replaced by 0 or 1 [29].

$$g(x,y) = \begin{cases} 1 \; if \; f(x,y) \geq T \\ 0 \quad otherwise \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \textit{Equation 3-4}$$

Multilevel thresholding can be considered as an extension of bilevel thresholding in which a gray level image f(x,y) is transformed to a multilevel image g(x,y), by several thresholds T1,T2,...,Tm, as follows [30].

$$g(x,y) = \begin{cases} 0 \quad if \; f(x,y) \leq T1 \\ 1 \quad if \; T1 < f(x,y) \leq T2 \\ \quad\quad . \\ \quad\quad . \\ \quad\quad . \\ m \quad if \; f(x,y) > Tm \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \textit{Equation 3-5}$$

## B. Segmentation by Edge-based Method

Edges typically occur on the boundary between two regions. The main features can be extracted from the edges of an image. Edge detection is used to find margins of object or region within an image. It is mostly used techniques in digital image processing. Edge-based segmentation methods detect discontinuities and produce a binary image contained edges and their background as the output of the image. In edge-based segmentation methods first detecting of all the edges and connected together to form the object boundaries to segment the required regions [31,39,26]. The most frequently used edge detection methods are: Sobel edge detection, Prewitt edge detection, Roberts edge detection, Laplacian of Gaussian (LoG) edge detection and Canny edge detection [2.6].

a) Roberts edge detection

It performs 2-D spatial gradient measurement on an image. In order to perform edge detection, the original image is convolved with the following two kernels [57]:

| | |
|---|---|
| 1 | 0 |
| 0 | -1 |

| | |
|---|---|
| 0 | -1 |
| -1 | 0 |

*Table 3-1 Roberts mask [57]*

The gradient can then be defined as [57]:

$$\nabla I(u,v) = G(u,v) = \sqrt{{G_u}^2 + {G_v}^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad \textit{Equation 3-6}$$

Where $I(u,v)$ is a point in the original image, $G(u,v)$ is a point in an image formed by convolving with the first kernel and G (u, v) is a point in an image formed by convolving with the second kernel.

**b) Sobel edge detection**

It performs 2-D spatial gradient measurement on an image and so emphasizes regions of high spatial frequency that correspond to edges [58]. The operator uses two kernels, which are convolved with the original image:

| | | |
|---|---|---|
| -1 | 0 | 1 |
| -2 | 0 | 2 |
| -1 | 0 | 1 |

| | | |
|---|---|---|
| 1 | 2 | 1 |
| 0 | 0 | 0 |
| -1 | -2 | 1 |

*Table 3-2 Sobel convolution kernels [58]*

The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation, Gu and Gv. The gradient magnitude is given by:

$$|G| = \sqrt{{G_u}^2 + {G_v}^2}$$

$$|G| = |G_u| + |G_v| \text{……………………………………………….. eq2.7}$$

**c) Prewitt edge detection**

Prewitt edge detector is an extension of the Roberts edge detector to a 3-by-3 neighborhood and is used for detecting vertical and horizontal edges in images.

| | | |
|---|---|---|
| -1 | 0 | 1 |
| -1 | 0 | 1 |
| -1 | 0 | 1 |

| | | |
|---|---|---|
| 1 | 1 | 1 |
| 0 | 0 | 0 |
| -1 | -1 | -1 |

*Table 3-3 Prewitt mask*

d) Laplacian of Gaussian (LoG) edge detection

The Laplacian of an image I (u, v) is defined as [57]:

$$\nabla^2 I = \frac{\nabla^2 I}{\nabla u^2} + \frac{\nabla^2 I}{\nabla v^2} \text{…………………………………} \textit{Equation 3-7}$$

The implementation of the Laplacian function is made through the mask:

| | | |
|---|---|---|
| 0 | -1 | 0 |
| -1 | 4 | -1 |
| 0 | -1 | 0 |

*Table 3-4 The Laplacian mask*

**C. K-Means Clustering**

Clustering is a method to divide a set of data into a specific number of groups [59]. The basic idea of K-means algorithm is to cluster the objects closest to them by clustering the K points in the space. It has two separate phases: In the first phase it calculates the k centroid and in the second phase it takes each point to the cluster which has nearest centroid from the respective data point [2.9]. There are different methods to define the distance of the nearest centroid and one of the most used methods is Euclidean distance. K-means is an iterative algorithm in which it minimizes the sum of distances from each object to its cluster centroid, over all clusters. Let us consider an image with resolution of X×Y and the image has to be cluster into k number of cluster. Let p (x, y) be an input pixel to be cluster and ck be the cluster centers. The algorithm for k-means clustering is following as [59]:

1. Initialize number of cluster k and center.
2. For each pixel of an image, calculate the Euclidean distance d, between the center and each pixel of an image using the relation given below.

$$d = \|P(x, y) - Ck\| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textit{ Equation 3-8}$$

3. Assign all the pixels to the nearest center based on distance d.
4. After all pixels have been assigned, recalculate new position of the center using the relation given below.

$$ck = \frac{1}{k}\sum_{y\in ck}\sum_{x\in ck} p(x, y) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \textit{ Equation 3-9}$$

5. . Repeat the process until it satisfies the tolerance or error value.
6. Reshape the cluster pixels into image.

### 3.6.4 Feature extraction

Feature extraction is the process of extracting this information from an image. It extracts a simplified representation of an image, to be used for classification. A good feature has selective information, which can differentiate one object from other objects [60]. The outcome of the feature extraction process can be used as an input to a further pattern recognition or classification technique in order to label, classify or recognize the content of the input image. There are different types of feature extraction techniques [60], such as texture, shape and color.

**A. Feature Extraction Based on Texture**

Texture feature extraction is one of the best techniques for a large image which contains a repetitive region. The texture is a group of pixels that has certain characterize. Texture can be defined as superficial phenomenon of human visual systems of natural objects [53]. This method is classified into two categories: spatial texture feature extraction and spectral texture feature extraction. Spatial texture is easy to use and understand and can be extract information from any shape. These features are very sensitive to noise and distortions. Spectral texture is robust and requires less computation. For efficient feature spectral texture require square region with sufficient size [53-34].

**B. Feature Extraction Based on Shape**

Shape features are very used for object recognition and shape description. The shape features extraction techniques are classified in to region based and contour based. Region-based methods use the whole area of an object for shape description and extracts feature from the entire region, while contour-based methods use only the information present in the contour of an object and calculate shape feature only from the boundary [54, 35].

**C. Feature Extraction Based on color**

Image feature extraction using color-based feature extraction is an important technique. The color histogram represents the most common method to extract color feature. Color features extraction should be based on a specific color space, such as HSV (hue, saturation, value), HSI (hue, saturation, intensity) or RGB (red, green, blue). The RGB color space is chosen in the present study to determine the first-, second- and third-order moments of 3 channels, in equations (2.1–2.3) [34,36].

$$\mu i = \frac{1}{N}\sum_{j=1}^{N} Pi,j \quad (i = R, G, B) \quad \ldots\ldots\ldots \quad \textit{Equation 3-10}$$

$$\sigma i = \frac{1}{N}\sum_{j=1}^{N}((Pi,j - \mu i)^2)^{1/2} \quad (i = R, G, B) \quad \ldots\ldots\ldots \textit{Equation 3-11}$$

$$\delta i = \frac{1}{N}\sum_{j=1}^{N}((Pi,j - \mu i)^3)^{1/3} \quad (i = R, G, B) \quad \ldots\ldots\ldots \quad \textit{Equation 3-12}$$

Where N is the total number of pixels in an image and p i, j is the level of the R, G or B component in one pixel. Nine color features are analyzed in equations (2.11–2.13) [36].

### 3.6.5 Classification

Classification techniques are used to classify different features available in the image. The objective of image classification is to identify the features occurring in an image in terms of the object. Image classification techniques are mainly divided in two categories: supervised image classification techniques and unsupervised image classification techniques [37]. Supervised classification requires human guidance. The analyst "supervises” the categorization of a set of specific classes by providing training statistics that identify each category. In Unsupervised classification, the raw spectral data are grouped first, based solely on the statistical structure of the data. Then the analyst must label each statistical cluster, placing them into the appropriate categories. There are different Supervised Image Classification algorithms. Some of them are the following.

#### 3.6.5.1 Support vector machines

Support vector machines are a set of supervised learning methods used for classification and regression. For a wide range of classification tasks, it is presently among the better performers among various classification models [63]. The classifier is used in the current image classification study due to its outstanding generalization capability and reputation of being a highly accurate paradigm [64]. SVM is very effective in high dimensional spaces. It also saves memory by using a subset of training points in the decision function [91, 7.17]. SVM classifies between two classes by constructing a hyperplane in high-dimensional feature space which can be used for classification. Hyper plane that differentiates the two classes in the best possible manner, which minimizes the upper bound on the generalization error, this actually results to avoid over fitting. it can be considered decision boundaries that classify data points into their respective classes in a multi-dimensional space.

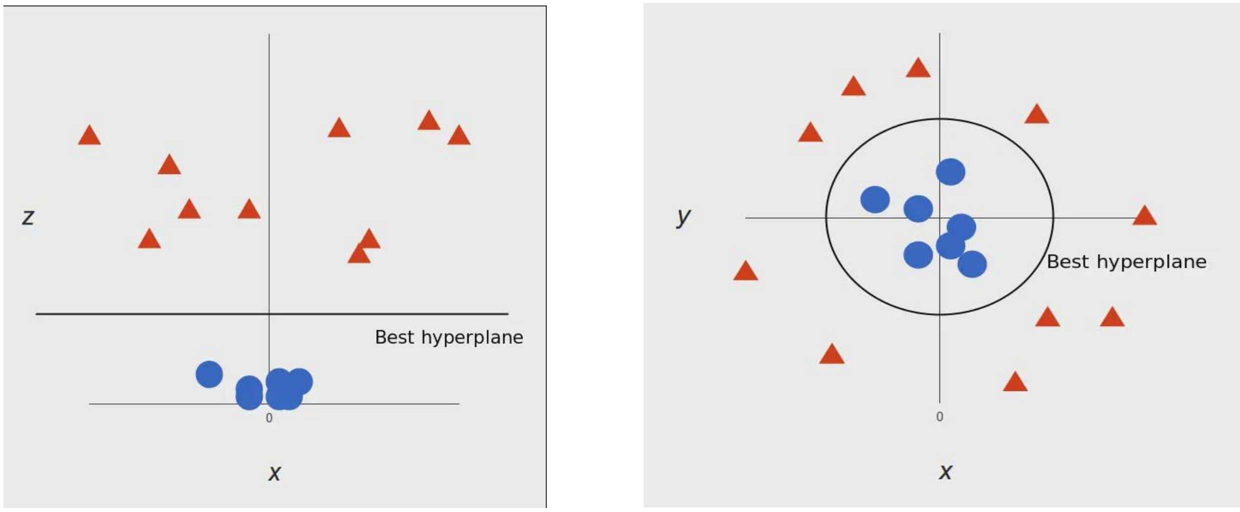



*Figure 3-9 SVM For linear [66]*

For nonlinear, Hyperplane in can be represented by equation [67]:

$w.x+b=0$ ……………………………………………………….*Equation 3-13*

w is weight vector and normal to hyperplane.

b is bias or threshold.

The SVM classifier satisfies the following conditions[60]:

$$h(xi) = \begin{cases} +1 & if\ w.x + b \geq 0 \\ -1 & if\ w.x + b < 0 \end{cases}$$ ………………………………*Equation 3-14*

### 3.6.5.2 K-Nearest Neighbors

K-Nearest Neighbors (k-NN) is a supervised machine learning algorithm. It is a simple, easy-to-implement supervised machine learning algorithm that can be used to solve both classification and regression problems the k-nearest neighbor (KNN) algorithm is a method for classifying objects based on closest training examples in the feature space [68]. KNN works on the bases of an assumption that objects of similar nature exist in close proximity. In KNN classification, a majority voting (as it is shown in figure 2.11) is applied over the k nearest neighbors to predict the output of a new dataset [69]. The triangle class label as shown in the figure 2.11 below has been assigned to the new data sample according to the majority nearest neighbors. Mathematical representation of the algorithm is given below [70]:

The first step is to calculate the distance between the new point and each training point. There are various methods for calculating this distance, of which the most commonly known methods are – Euclidian, Manhattan and Hamming distance.

**Euclidean distance**

Euclidean distance is the square root of the sum of the squared differences between two points x,y and it is calculated as follows:

$D(X, Y) = \sqrt{((X1, Y1)^2) + ((X1, Y1)^2) \dots \dots .. + ((Xn, Yn)^2)}$ …………………*Equation 3-15*

$= \sqrt{\sum_{i=1}^{n}(Xi - Yi)^2}$

**Manhattan Distance:**

Manhattan Distance is the sum of the absolute difference between two points and it is calculated as follows:

$D(X, Y) = \sum_{i=1}^{n} |(Xi - Yi)|$ ……………………………………………*Equation 3-16*

**Hamming Distance:**

Hamming Distance is used for categorical variables. If the value (x) and the value (y) are the same, the distance D will be equal to 0 . Otherwise D=1.

$DH = \sum_{i=1}^{k} |Xi - Yi|$ ……………………………………………*Equation 3-17*

$x = y \Rightarrow D = 0 \qquad x \neq y \Rightarrow 1$

The second step is to select the k value. This determines the number of neighbors we look at when we assign a value to any new observation.

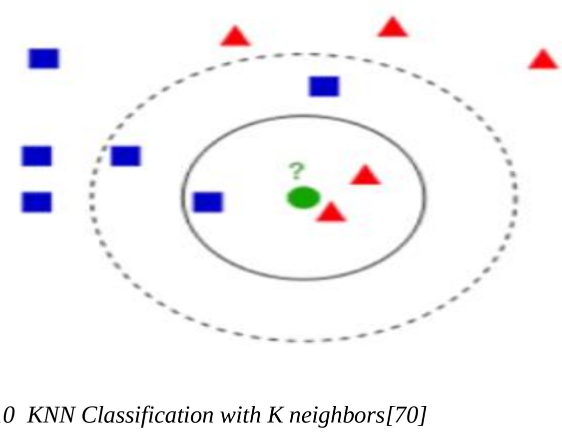



*Figure 3-10 KNN Classification with K neighbors[70]*

## 3.7 Related Works

In this section, related works of different researchers in the area of human skin disease identification using image processing and machine learning system were reviewed. Several researchers have developed systems related to the detection and classification of skin diseases using different techniques, among them the literatures in specific to image processing and machine learning techniques are reviewed as follows.

### 3.7.1 Foreign works

Sumithra Ra, Mahamad Suhilb, and Guruc, [71] conduct a research on a novel approach for automatic segmentation and classification of skin lesions. They prepare dataset of 726 lesion samples from 5 different classes of skin diseases images are collected through internet. In this research the researcher proposed methodology to design and develop a computer vision-based system for segmentation and classification of skin lesions along with extraction of discriminating set of features from skin lesions for efficient classification. Initially they segmented the lesion areas using region growing method, and Color and texture features are extracted to represent segmented lesion areas. Then the classification is performed with SVM, KNN as well as fusion of SVM and KNN Classifiers. The results are 46.71% and 34% of F-measure using SVM and k-NN classifier respectively and with 61% of F-measure for fusion of SVM and KNN. Finally, they have concluded that, an improvement in classification might be achieved through the use of different classifiers such as ANN classifier, PNN classifier etc., separately and in combination. Therefore, the performance of results is affected by the number of dataset and feature selection methods.

N. Alamdari, [15] studied detection and classification of Acne Lesions in Acne Patients, which focused on designing a Mobile Application that focuses on common chronic skin disease of Acne diseases. The aim of this paper is to find a proper computational imaging method for automatic detection of acne using images that are taken by cell phone and then the classification of the different type of acne lesions from each other. A total of 35 images were used to perform the segmentation and classification of the different types of acne lesions for evaluating the methods. For the Image Processing they used  K-means clustering was used to divide an image into regions, each of which has a rationally similar visual appearance or that matches objects or parts of objects. 3-D Gaussian methods have been used to smooth the image, and then the rangefilt MATLAB command was applied to compute the local range of the image. To perform HSV-based segmentation, a modified version of “Color Blob Utility with Automatic Thresholding and Tolerance Calculations” was used. The classification is first done using fuzzy c-means (FCM) method, the accuracy of differentiating acne scarring from active inflammatory lesions is 80%. In the second phase classification is done using SVM classifier which achieved an accuracy of 66.6%. The performance accuracy of classifying normal skins from detected acnes is 100% using fuzzy-c-means clustering. Finally, they have concluded future research can apply these methods to acne images and comparing the results and combining the successful algorithms to get higher accuracy. But, limited number of images to perform the segmentation and then classification tasks, therefore accuracy (around 66.6%) is not so good.

Kumar, V. B., Kumar, S. S., & Saboo, V. [72], conduct a research on Dermatological Disease Detection Using Image Processing and Machine Learning. The research used a dual stage approach which combines Computer Vision and Machine Learning on clinically evaluated histopathological attributes to accurately identify the disease. For this research they were taken the dataset used for training from the learning data repository of University of California, Irvine. 67% of the data is used for training and 33% is used for testing the models. to improve the accuracy of feature extraction, eight different preprocessing algorithms they were used. The algorithms used were converting to grey scale image, sharpening filter, median filter, smooth filter, binary mask, RGB extraction, histogram and sobel operator. In the first stage, the image of the skin disease is subject to various kinds of pre-processing techniques followed by feature extraction. The second stage involves the use of Machine learning algorithms to identify diseases based on the histopathological attributes observed on analyzing of the skin. Nonlinear models like ANN and DT learns the underlying pattern and gives better accuracy. Finally, the novel method of using a dual stage system has given very promising results in identification of skin diseases with accuracies of up to 95%.But; the system suffers from inaccuracies when it is tasked with detection of diseases on varying skin colors.

Li-sheng, Quan, & Tao [17], conduct a research on Skin Disease Recognition Method Based on Image Color and Texture Features. The authors proposed a method for skin disease detection and classification using GLCM for feature extraction and SVM for classification. They used grey-level co-occurrence matrix (GLCM) method to segment images of skin disease. Then they used support vector machine (SVM) classification method, three types of skin diseases were identified. Finally, their method recognized three types of diseases, namely, herpes, dermatitis, and psoriasis. Their evaluation result is 85%, 90%, 95% of the recognition rate respectively.

Sam, Philip, Nartey, & Nti [73] proposed A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks. They used TensorFlow framework for detecting skin diseases. Researchers used CNN for feature extraction and web-based system to classifying and Diagnosis Atopic dermatitis, Acne vulgaris and Scabies. Disease identification accuracy of 88% for atopic dermatitis, 85% for acne vulgaris, and 84.7% for scabies. The overall classification accuracy is 88%. However, the data size for the study is limited and the methods in this study are innovations of the traditional preprocessing method. Therefor Techniques to enhance the accuracy are not effective.

### 3.7.2 Local works

Selomie [16], proposed deep learning algorithm and level set method to develop skin lesion segmentation. The author used convolution de-convolution neural network and contour level set method for segment dermoscopic skin lesion images. Vector median filter is used to facilitate the segmentation border detection. In the first step they applied preprocessing dermoscopic images with robust method of image enhancement for RGB images, prepare image data set including data augmentation regularization to overcome over fitting, test the performance of semantic segmentation of the trained network before integrating to the level set method and finally apply CDNN plus level set method for segmentation. The performance evaluations on the proposed skin lesion segmentation method are pixel wise average measurements validated against ground truth for test data set are 94.8% intersection over union, 98.80% specificity, 94.84% sensitivity, 97.84% positive predicted value and 95.58% negative predicted value. But, there is gap on skin lesion segmentation using deep learning and level set method, since the problem is a fatal issue of public health.

Endalkachew [69], presented a computer aided diagnosis system for the detection of melanoma skin cancer using a novel mathematical scheme. The research proposed a holistic representation of skin color images to extract useful features for use in effective segmentation of melanoma lesions. For this research they were taken from three databases, PH2 200 dermoscopic images, 160 are benign (which include 80 common nevi and 80 atypical nevi) and 40 melanoma lesions with their respective annotations from experts. The segmentation scheme is preceded by a processing stage composed of noise filtering color space transformation. Vertex component analysis and principal component analysis are integrated to form a hybrid approach for unmixing and feature dimension reduction. An optimized feature selection technique is also used to obtain the best achievable performance in effectively detecting the lesions. Support vector machine (SVM) along with geometrical and color feature threshold values are integrated to make effective detection of melanoma lesions. Finally, the proposed approach scored 98.6% accuracy. Finally, the author concluded the study demonstrating why holistic analysis of colors is more important than their serial equivalents.

Bezawit Lake[47], proposed an approach for cattle disease diagnosis by integrating image processing using deep learning with an expert system. The classification model used is a convolutional neural network with three convolutional and two fully connected layers. In the classification phase the trained model is used to classify the input images. The developed classification model trained on 3990 data set collected from different sources. To increase the data set they applied different augmentation techniques. They split the dataset into 90% for training and 10% for testing. Finally, the proposed approach scored 95 % accuracy. Generally, study was classified cattle skin disease into its three main classes (Lumpy skin disease, Ringworm and Wart). But, the need for classifying lumpy skin disease images into normal, mild and severe based on their severity stages.

### 3.7.3 Summary

In summary, the above studies use different machine learning techniques in order to detect or classify human and animal skin disease. However, reviewed literature proposed methods mainly aim at the identification of only skin disease types, which makes them difficult to apply for one skin disease classification based on severity stages. Based on the previous related work reviewed above, we tried to design a detection model for classifying lumpy skin disease images into normal, mild and severe based on their severity stages. To this end, the following basic tasks are accomplished. Firstly, the sample images of Lumpy Skin Disease need to be preprocessed. Secondly, the preprocessed image is segmented and made corresponding geometric transformation. Based on this, Lumpy Skin Disease features are extracted using CNN. Finally, the Lumpy Skin Disease identified by utilizing the support vector machine (SVM) and Random Forest (RF) method in order to improve identification accuracy.

# CHAPTER THREE

# METHODS AND ALGORITHMS

## 4.1 Overview

The aim of this study is to apply image processing and machine learning classification algorithms in order to detect animal Lumpy skin disease. This chapter is organized to explain architecture, approaches and methods and algorithms used as per the proposed architecture by the research. Accordingly, first we present the proposed architecture of the system in section 3.2. Then the remaining sections present, methods and algorithms used for implementing and experimenting image preprocessing, image segmentation, feature extraction and classification.

## 4.2 The proposed Architecture

The proposed architecture in this study is presented in figure 3.1. It deals with animal Lumpy Skin Disease detection using image processing and machine learning. It involves processes like image preprocessing, image segmentation and feature extraction and finally classification of images.

Image preprocessing includes a sequence of steps such as, resizing the image to a (200×200) size. To improve contrast in image we applied Histogram Equalization by effectively spreading out the most frequent intensity values. Then noise removal using median filtering. After preprocessing, image data augmentation applied on the dataset to increase the train dataset and to overcome overfitting problem. In the second step image segmentation applied to find region of interest and to separate the foreground and background of image. The third step is feature extraction; it is performed using CNN. CNN Feature extraction model has a convolutional layer, pooling layer, and fully connected layer, to extract relevant features. Finally, we apply the RF, SVM and SoftMax for classification function to classify into a predefined set of classes. The testing phase follows similar procedures with the training phase. The proposed approach is shown in the below Figure 3.1.

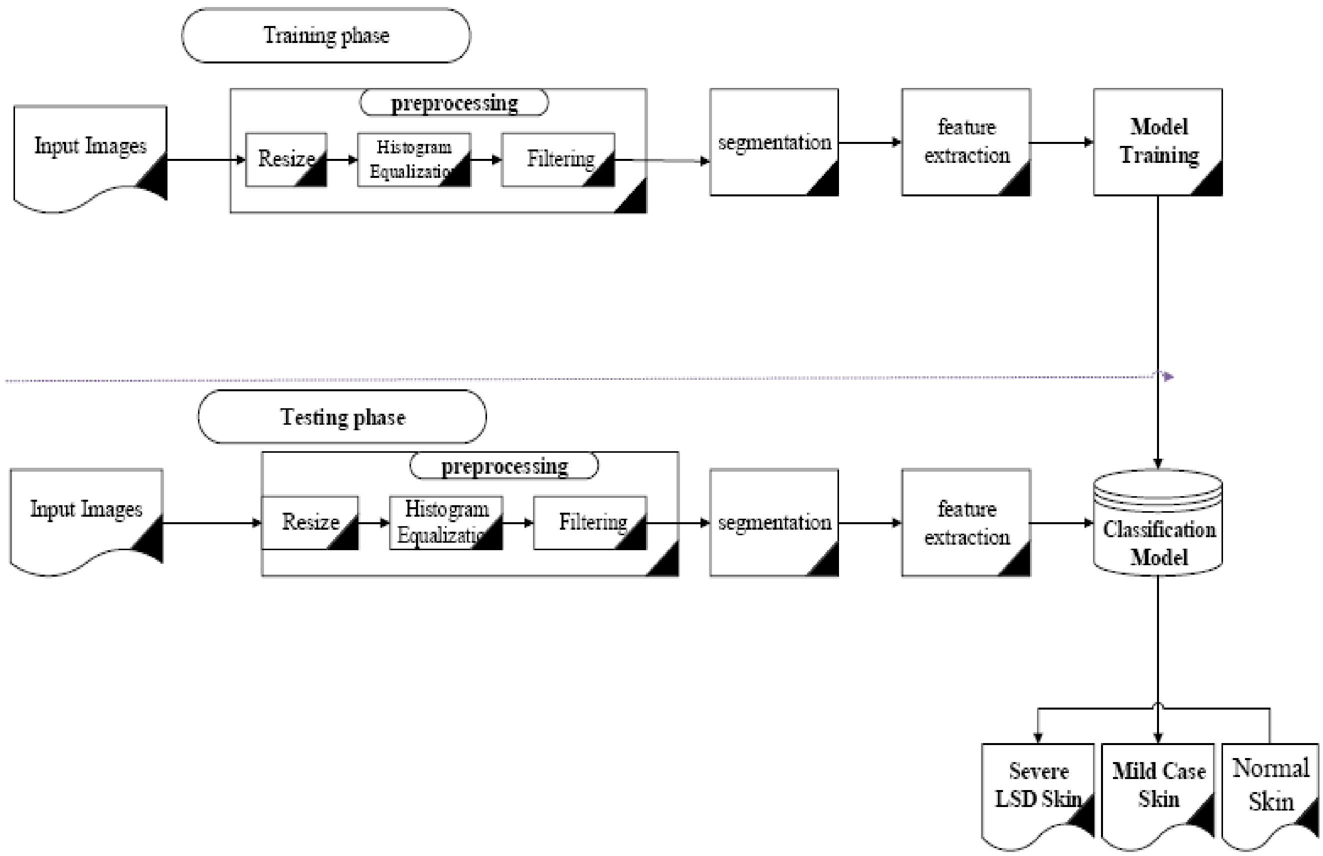



*Figure 4-1 Proposed architecture*

## 4.3 Dataset Preparation

### 4.3.1 Image acquisition

In this study we acquired the datasets from Oromia region Bale zone Medawelabu wereda and Arsi zone Chole wereda Livestock production offices using smart phone in the form of JPEG (Joint Photographers Expert Groups) file format. To maximize the number of collected datasets we used additional datasets from public source using google search engine and we transform the collected image data from both sources by cropping the area where Lumpy Skin Disease are present. By the help of veterinary Doctor, we divided the dataset into Severe Lumpy Skin Disease, Mild Lumpy Skin Disease and Normal Skin.

The total number of images taken for this study, from each class; Normal skin, and Severe Lumpy Skin Disease infected skin and Mild Lumpy Skin Disease infected skin, are shown in Table 3.1 below

Table 3-1: Total dataset used in this study

| No | Category | Number of collected image data | After transformation |
|---|---|---|---|
| 1 | Normal skin | 120 | 150 |
| 2 | Mild Case Lumpy Skin Disease infected skin | 80 | 150 |
| 3 | Severe Case Lumpy Skin Disease infected skin | 50 | 150 |
| 3 | Total | 250 | 450 |

*Table 4-1 Total dataset used in this study*

Here under in figure 3.2 sample images that depicts the different levels of Lumpy Skin Disease infected cattle skin is given.

(A) (B) (C)

*Figure 4-2 A Normal skin ,B, Mild case lumpy skin dieases and C, Severe lumpy skin disease*

## 4.4 Image Pre-Processing

The acquired image passes through image preprocessing, which is an essential step of detection in order to enhance the quality of original image by removing unrelated and surplus parts such as noise in the background of images. In this step the following image preprocessing steps are undertaken.

### 4.4.1 Resizing the image

At first all images were resized to a size of 200 by 200 pixels to make them compatible, and have a uniform size for all images because the number of features that extracted from each image must be unified. It can reduce the time of training of a neural network as more is the number of pixels in an image more is the number of input nodes that in turn increases the complexity of the model. The algorithm for image resizing is depicted in Algorithm 3.1

| |
|---|
| Input: images |
| Output: resized_image (200,200) |
| Begin: |
| for img in images: |
|     resized_ image=resize (img, resize=200x200) |
|     return resized_image |
| END |

*Algorithm 4-1 Image processing of resized image*

### 4.4.2 Conversion of RGB image to Grayscale Format

For simplifying image processing and analysis, there is a need to convert RGB image to grayscale image. Grayscale is a simple one channel image with values ranging from 0 to 255 that represent the intensity of pixels. RGB image to grayscale conversion helps to work well with many image processing algorithms because grayscale images are easy to process than RGB images. To convert RGB (red/green/blue) image to grayscale, weighted averaging method is used as shown in the following equation [95]:

*New grayscale image = ((0.3 * R) + (0.59 * G) + (0.11 * B)). ……….Equation 4-1*

According to this equation:

Red has contributed 30%,

Green has contributed 59% which is greater in all three colors and

Blue has contributed 11%.

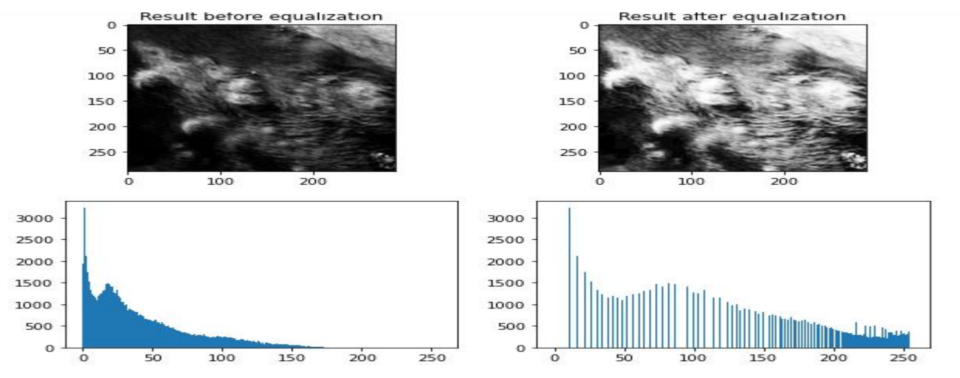
| |
|---|
| **Input:** Colure Images |
| **Output:** Grayscale Images |
| **Begin:** |

| |
|---|
| For Each Pixel in Image:<br><br>Red = Red Pixel.<br>Green = Green Pixel.<br>Blue = Blue Pixel. |
| Gray = (Red*0.3+ Green*0.59 + Blue*0.11) / 3<br>Red Pixel. = Gray<br>Green Pixel. = Gray<br>Blue Pixel. = Gray |
| Return Grayscale Image |
| **END** |

*Algorithm 4-2 Conversion of RGB image to Grayscale Format*

### 4.4.3 Histogram equalization

Histogram equalization is a method to process images in order to adjust the contrast of an image by modifying the intensity distribution of the histogram. This method usually increases the global contrast of images when its usable data is represented by close contrast values.




(A) (B)

*Figure 4-3 The effect of histogram equalization on infected Lumpy Skin Disease skin (A) Un_equalized and (B) Equalized*

### 4.4.4 Image filtering

For removal of noise, numbers of filtering techniques are there in literature. Basically, they are of two types: Linear filtering techniques and Non-linear filtering techniques. In this study for smoothing image from noise we proposed median filtering and Gaussian filtering. The median filter and Gaussian filtering are very effective at removing impulse noise. The median filter is the one type of nonlinear filters. It is very effective at removing impulse noise, the “salt and pepper” noise, in the image. It is very widely used in digital image processing because, under certain conditions, it preserves edges of the images while removing noise [74]. For a given set of random variables, X = (X1, X2, - - -, XN) with the order X1, X2, ---, XN are random variables, which sorted in an increasing order. Where k is the median Rank, the median value can be calculated as shown below [60]:

$$Median(X) = \begin{cases} X_{k+1,} \; for \; N = 2k+1 \\ \frac{1}{2}(X_k + X_{k+1}), \;\; for \; N = 2k \end{cases} \quad \text{……… } \textit{Equation 4-2}$$

Gaussian filters are a class of linear smoothing filters with the weights chosen according to the shape of a Gaussian function. The Gaussian smoothing filter is a very good filter for removing noise drawn from a normal distribution. Gaussian kernel coefficients are sampled from the 2D Gaussian function.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e_{2\sigma^2}^{\underline{-x^2+y^2}} \text{……………….. } \textit{Equation } \text{4-3}$$

function.

### 4.4.5 Data augmentation

Data augmentation is an effective technique for improving the accuracy of modern image classifiers [98]. It is an important part of training a machine learning model, especially when the training images are limited. The augmented data represent a more comprehensive set of possible data points, thus minimizing the distance between the training and test sets [76]. There are various data augmentation techniques. The selected data augmentation techniques were: flipping images horizontally or vertically, rotating images at 40 degrees, rescaling outward or inward, randomly cropping, translating by width and height shifts, whitening, shearing, zooming and adding Gaussian noises to prevent model overfitting and enhance learning capability.

## 4.5 Image segmentation

The goal of segmentation process is to partition an image into regions that are homogeneous with respect to one or more characteristics or features such as luminance, color, and texture. The result of image segmentation is a binary mask at the location of lesion. Accurate segmentation of medical images is very important for the analysis and diagnosis of abnormalities in different parts of the body [77]. There are many methods for image segmentation. The most common images segmentation techniques are region segmentation techniques that look for the regions satisfying a given homogeneity criterion, and edge-based segmentation techniques that look for edges between regions with different characteristics [28]. Thresholding is region segmentation method a threshold is selected, and an image is divided into groups of pixels having values less than the threshold and groups of pixels with values greater or equal to the threshold. There are several thresholding methods: global methods based on gray-level histograms, global methods based on local properties, local threshold selection, and dynamic thresholding [28].

For this work, we have proposed Adaptive thresholding, Edge-Based Segmentation and Otsu segmentation method.

#### 4.5.1.1 Adaptive Thresholding

Adaptive thresholding is a technique of finding the different threshold values for different regions of the image. Adaptive Thresholding Approach is dividing the image into n x m blocks: In this case, the image is divided into n x m blocks, overlapping or nonoverlapping as the objective desires, where $\{n, m \in N| \ n, m > 0\}$. Then global thresholding is applied on each block which provides varying thresholds for each block [78].

#### 4.5.1.2 Edge-Based Segmentation

Edge is a boundary between two homogeneous regions. Edge detection refers to the process of identifying and locating sharp discontinuities in an image. Edge detection is the most common approach for detecting meaningful discontinuities in gray level [108, 109]. To detect consequential discontinuities in the gray level image is the important common approach in edge detection. edge detection techniques are involved is automatic character recognition. Edge detection is used for object detection which serves various applications like medical image processing, biometrics etc. [79] The three fundamental steps of edge detection are Image

Smoothing, Detection of edge points and Edge localization [79]. There are many edge detection techniques in the literature for image segmentation. The most commonly used discontinuity-based edge detection techniques are Roberts edge detection, Sobel Edge Detection, Prewitt edge detection, Kirsh edge detection, Robinson edge detection, Marr-Hildreth edge detection, LoG edge detection and Canny Edge Detection. To find edges by separating noise from the image before find edges of image the Canny is a very important method [7.1]. The Process of Canny edge detection algorithm can be broken down to 5 different steps [110, 111]:

1. Apply Gaussian filter to smooth the image in order to remove the noise
2. Find the intensity gradients of the image
3. Apply gradient magnitude thresholding or lower bound cut-off suppression to get rid of spurious response to edge detection
4. Apply double threshold to determine potential edges
5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

Otsu method is one of the most successful region-based segmentation methods for automatic image thresholding because of its simple calculation.

In Otsu's method we minutely explore the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes [6.7]:

$$\sigma^2{}_W(t) = w_0(t)\sigma^2{}_0(t) + w_1(t)\sigma^2{}_1(t) \quad \ldots\ldots\ldots\ldots \qquad \textit{Equation 3-4}$$

Aforementioned weights $W_0$ and $W_1$ are the probabilities of the two classes separated by a threshold t and $\sigma^2{}_0$ and $\sigma^2{}_1$ are variances of these two classes. Otsu formulates that minimization of the intra-class variances is correlative to maximization the inter-class variance as [80]:

$$\sigma^2{}_b(t) = \sigma^{2-}\sigma^2{}_w(t)=w_1(t)w_2(t)[\mu_1(t)- \mu_2(t)] \quad \ldots\ldots\ldots\ldots\ldots \qquad \textit{Equation 4-5}$$

That is expressed in the terms of class probabilities $w_i$,and class means $\mu_i$.

The class probability, $w_1$ (t) will then be calculated from the histogram t as follows [80]:

$$w1(t) = \sum_{i=0}^{t} P(i) \quad \ldots\ldots\ldots\ldots\ldots \qquad \textit{Equation 4-3}$$

*Whereas, the class mean $\mu_1$ (t) is given as :*

$$\mu1\ (t)\ = \sum_{i=0}^{t} P(i)(i) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad \textit{Equation 4-6}$$

## 4.6 Feature Extraction

Feature extraction is a technique by which unique features of images are extracted and distinguishing basic characteristic or attribute of an image. By Feeding huge entire of digital images to a classifier is time-consuming method for classification. To finding a way to minimize the amount of data, quantitative information is extracted from the objects to be analyzed in the image [81, 83]. It is the most important step in image processing. feature extraction techniques are classified as low-level feature extraction and High-level feature extraction. Low-level feature extractions are based on finding the points, lines, edge, etc. while high level feature extraction methods use the low-level feature to provide more significant information for further processing of Image analysis. Mostly high-level feature extraction method uses the Artificial Neural Network (ANN) to extract the feature in multiple layers [33]. In recent years, deep convolutional neural networks (CNN) become very popular in feature learning, which can extract deep representation of training data, have achieved impressive performance within short time in image classification specially in medical image detection and classification systems [84]. The different CNN architectures include LeNet, AlexNet, VGGNet, GoogleNet, ResNet, ZFNet are used for future extraction [65]. For our research We proposed to develop CNN model for feature extraction. CNN Architecture have several layers like convolution layer, pooling layer, Rectified Linear Unit layer, Fully Connected layer.

**convolution layer:**

The prime purpose of convolution is to extract distinct features from the input. It has several filters that perform the convolution operation. neurons that connect to small area of the input image is known as filters or masks. Filter size are specified like $3 \times 3$, $5 \times 5$, $7 \times 7$, etc. and the number of weights used to the filter is $h \times w \times d$, where 'h' is the height of an image, 'w' is the width of an image and 'd' is the depth of an image [85]. Each convolutional layer has a set of filters, and each filter will produce a separate 2-dimensional map. These separate activation maps are stacked to produce the output of the convolutional layer [86]. The width and height of the filters are hyper-parameters, while the depth of the filters must be equal to the depth of the input image. Filter hyperparameters, which all will affect the size of the output image, are [87]:

- **Dimensions of a filter**: a filter of size $h \times w$ applied to an input containing C channels is $h \times w \times C$ volume that performs convolutions on an input of size $I \times I \times C$ and produces an output feature map (also called activation map) of size O×O×1. Therefore, the application of K filters of size h×w results in an output feature map of size O×O×K.

- **Stride**: For a convolutional or a pooling operation, the stride S denotes the number of pixels by which the window moves after each operation.
- **Zero-padding**: Zero-padding denotes the process of adding P zeroes to each side of the boundaries of the input. Most commonly, zero-padding is used to preserve the size of the input size to the output.
- **Tuning hyperparameters**

  By noting I the length of the input volume size, F the length of the filter, P the amount of zero padding, S the stride, then the output size O of the feature map along that dimension is given by:

$$O = \frac{I - F + Pstart + Pend}{S} + 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . \textit{Equation 4-7}$$

**Pooling Layer**

pooling layer is reducing the number of parameters and computation in the network by reducing the spatial size of the image representations. It usually mediates between several convolutional layers. There are different types of pooling, but Max-pooling and average-pooling are the most frequently used pooling strategies in CNNs.

**ReLU Layer**

The rectified linear unit layer (ReLU) is an activation function used on all elements of the volume. Increases the non-linearity of the network while also removing negative values from the activation maps. the activation function to the input x are[86]:

$$f(x) = max(0, x) \ldots\ldots\ldots\ldots\ldots\ldots . \textit{Equation 4-8}$$

**Fully-Connected Layer**

The fully connected layer operates on a flattened input where each input is connected to all neurons. The layers are usually found towards the end of CNN architectures and can be used to optimize objectives such as class scores. in this study we omitting the fully-connected layers and using the output from the last max-pooling layer as feature vectors for each image.

The proposed model used for extract feature by transfer learning approach based on the VGG16 architecture for classification of Animal Lumpy Skin Disease. The architecture of the CNN model used in this study is schematically illustrated in FIG 3.4. The architecture of the model has different layers which are responsible for feature extraction from the input image. The input contains 200× 200 ×3 neurons, representing the RGB values for a 200× 200 ×3 image. we use filters with 3 × 3 with a stride length of 1 pixel to extract feature maps, followed by a max pooling operation conducted in a 2 × 2 region, with stride 2. The first Convolutional layer accepts 200x200x3 image and have filter with 3x3x3 with a stride length of 1 pixel to extract 32 feature maps. The max polling layer will perform down sampling operation along the spatial dimensions (width, height), resulting in volume 100x100x32. The second conv layer accept the result of the first conv layer 100x100x32 and use 3x3 local receptive fields, resulting in 64 feature maps. Max poling follows to perform down sampling and result 50x50x64 volume. The third conv layer accept the result of the second conv layer 50x50x64 and use 3x3 local receptive fields, resulting in 128 feature maps. Max poling follows to perform down sampling and result 25x25x128 volume. The final fully connected layer computes the class scores, resulting in volume of size 1x1x3, where the 3 numbers correspond to a class score, among the 3 categories of our dataset.

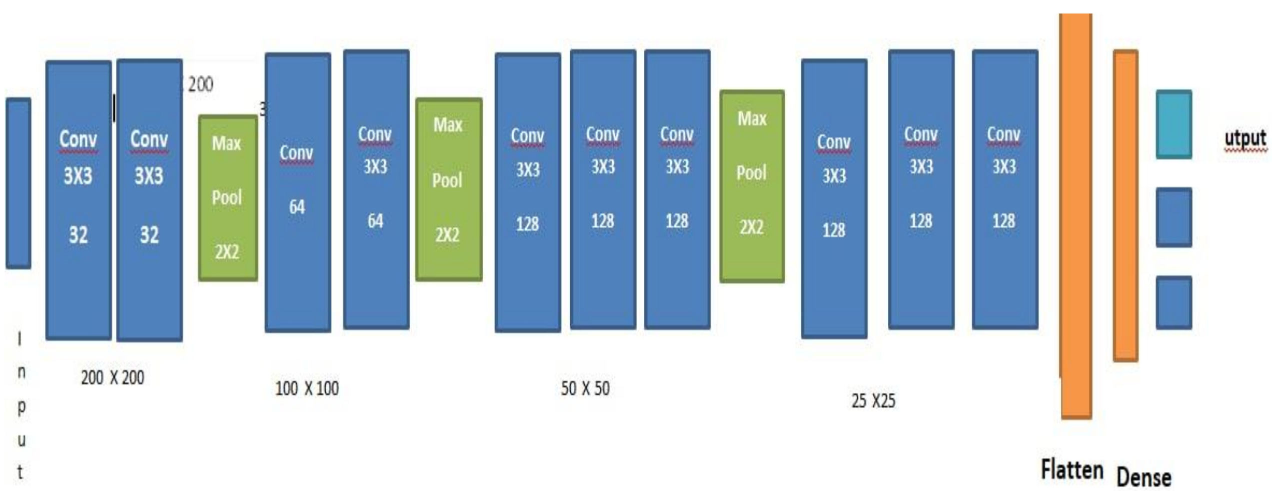



*Figure 4-4  proposed CNN architecture includes an input layer, multiple alternating convolutions and max-pooling layers, flatten, dense  and classification layer*

## 4.7 Classification

Image classification is a fundamental problem in pattern recognition. Classification involves assigning label to the image, based on the feature vector. After extracting features, the role of classification is to construct a detention model using different classification algorithms. The extracted features are used for the recognition and classification of Normal, Mild and Severe Lumpy Skin Disease lesions. The classification consists of two steps: training and testing. In this work, the division ratio of training to testing in percentage is 80:20. In training, the feature extracted is applied as an input to the classifier and the corresponding labels form the target outputs. The classification scheme then learns the mapping for separating the three classes from each other. In the testing step, new image features are applied to the trained network which then estimates the image class. In literature, we can find a number of classifiers. We find that in previous studies, researchers have used different types of classification algorithms for skin disease detection like SVM, CNN, and RF and they and obtained good accuracy [88,73,99]. So, we proposed in this study to test the following ML algorithms performance.

### 4.7.1 Softmax

Softmax is a mathematical function that converts a vector of numbers into a vector of probabilities, where the probabilities of each value are proportional to the relative scale of each value in the vector[96]. the softmax function is used to normalize the outputs, converting them from weighted sum values into probabilities that sum to one. Each value in the output of the softmax function is interpreted as the probability of membership for each class. It is also very fast to train and predict [67].

### 4.7.2 **Support vector machines**

Support vector machines are a set of supervised learning methods used for classification and regression. For a wide range of classification tasks, it is presently among the better performers among various classification models [63]. the classifier is used in the current image classification study due to its outstanding generalization capability and reputation of being a highly accurate paradigm [64]. SVM is very effective in high dimensional spaces. It also saves memory by using a subset of training points in the decision function [65]. SVM classifies between two classes by constructing a hyperplane in high-dimensional feature space which can be used for classification. hyperplane that differentiates the two classes in the best possible manner, which minimizes the upper bound on the generalization error, this actually results to avoid over fitting. it can be considered decision boundaries that classify data points into their respective classes in a multi-dimensional space.

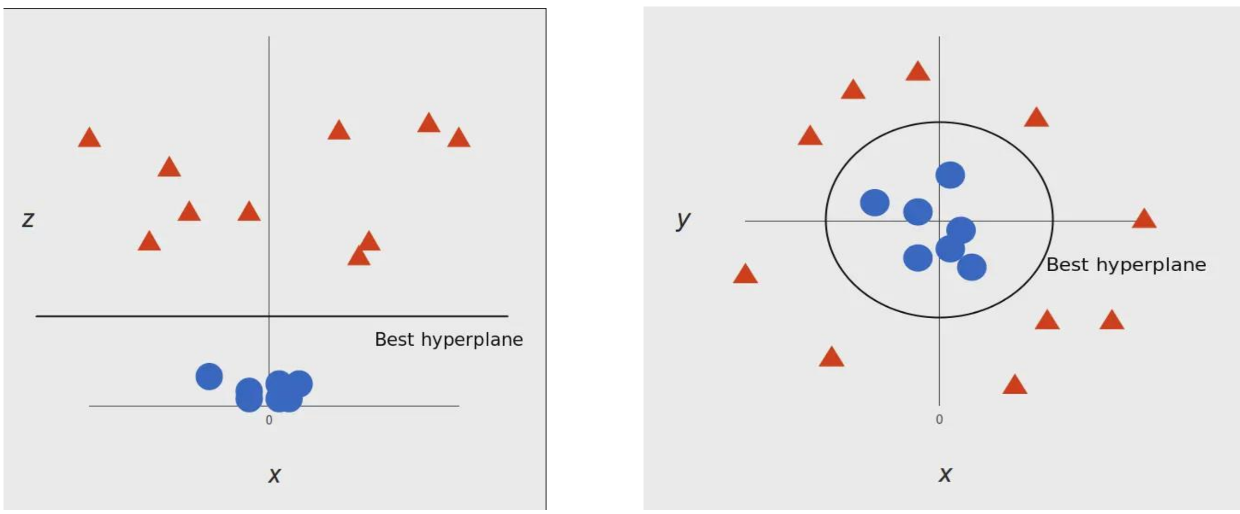



*Figure 4-5 SVM For linear [89]*

Hyperplane in can be represented by equation[7.18]:

$w.x+b=0$ ………………… *Equation 4-9*

w is weight vector and normal to hyperplane.

b is bias or threshold.

The SVM classifier satisfies the following conditions[7.19]:

$h(xi) = \begin{cases} +1 & if\ w.x + b \geq 0 \\ -1 & if\ w.x + b < 0 \end{cases}$ ………………*Equation 4-10*

### 4.7.3 Random forest

Random forest is an ensemble learning algorithm in machine learning. It is a widely used machine learning method with high prediction accuracy [90]. Random Forest (RF) is a method for classification and regression that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees [91]. Each decision tree votes for the classification of a given data. The random forest algorithm then accepts the classification which got a maximum number of votes from an individual tree [92] random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction**.** [93]. Below you can see how a random forest would look like with N numbers of trees:

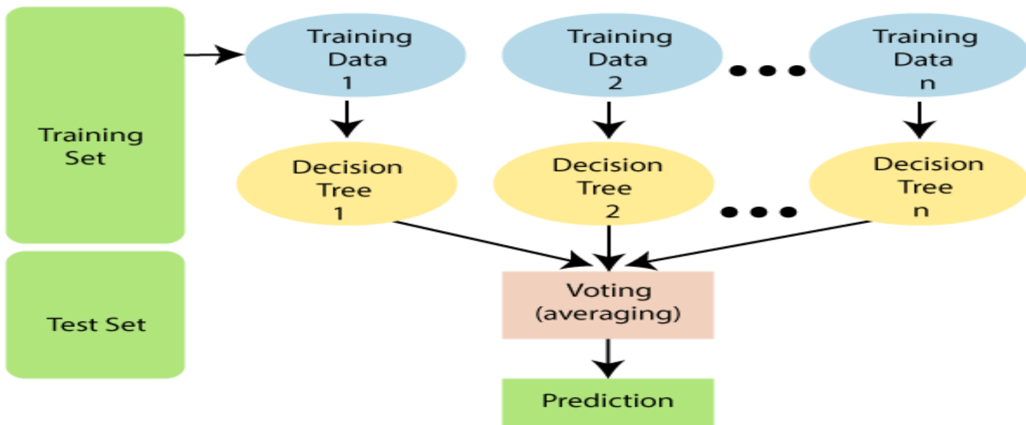



***Figure3.7:*** *Random Forest* ***[94]***

## 4.8 Evaluation metrics

To evaluate the performance of the protype we used different measures such as Accuracy, Recall, Precision and F-score. These metrics are based on the number of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) samples.

Accuracy is defined as the ratio of the correctly recognized (either positive or negative) to the total number of samples[51]:

$Accuracy(\%) = \frac{TP+TN}{TP+FN+TN+FN} * 100 \ldots\ldots\ldots\ldots$ *Equation 4-11*

Precision is a metric that is used to quantify the number of correct positive predictions made and it is the ratio of correct positive predictions out of all positive predictions made [99].

$Precision\% = \frac{TP}{TP+FP} * 100 \ldots\ldots\ldots\ldots\ldots\ldots\ldots$ *Equation 4-12*

Recall is a metric that is used to quantify the number of correct positive predictions made out of all positive predictions that could have been made. recall indicates the missed positive predictions [99].

$Recall\% = \frac{TP}{TP+FP} * 100$……………………*Equation 4-4*

F-score is a single measure that is used to summarize model performance. It can be used to level out the performance of the model in the case where one of the matrices is high and the other is low [99].

$F - Score = 2\frac{Precision * Recall}{Precision + Recall}$……………………*Equation 4-14*

Where; TP – True Positive

TN – True Negative

FP- False Negative

FN- False Negative

# CHAPTER FOUR

# IMPLEMENTATION AND DISCUSSION OF RESULT

## 5.1 Overview

In this chapter, we discuss the experiments carried out to implementation of the animal Lumpy Skin Disease detection system. As described in chapter three, the detection of animal Lumpy Skin Disease has six components. They were image acquisition, image preprocessing, image segmentation, feature extraction, classification, and testing. Accordingly, results achieved in the classification process and the system performance discussed.

The implementation is done using Python (version 3.8) environment, as well as Keras with TensorFlow backend was used to build up and train a CNN model. Intel(R) Core(TM) i5-10210U CPU @ 1.60GHz, 2112 Mhz, 4 Core(s), 8 Logical Processor(s) were used to perform computations.

## 5.2 Model Evaluation

The model performance was evaluated with accuracy and loss function for the training and test datasets in the absence or presence of applying segmentation techniques. The characteristics derived from confusion matrices are used to compare individual class prediction. In section 1.7.5 was discussed in this study.

In addition, we clearly show the difference on the accuracy of our model in training phase and testing phase, and the difference in performance of our model while applying the Softmax classifier, RF classifier and SVM classifier separately. And, we also evaluate the effect of segmentation on the performance of the CNN model.

## 5.3 Dataset used for experimentation

We collected 250 Lumpy Skin Disease and normal cattle skin images from Oromia region Bale zone Medawelabu Wereda Livestock production offices and from searching Internet using google search engine. The images were collected by using a digital mobile camera in certain conditions. After collecting some dataset, we transform the collected image from both sources by cropping 200X200 pixels size the area where Lumpy Skin Disease are present. Then data augmentation applies on the collected dataset to minimize over fitting problem. From all dataset images 80% of the dataset used for training and 20% used for testing.

A total of 250 of Lumpy Skin Disease cattle skin images and Normal cattle skin images are prepared to training and testing the proposed model. By the help of veterinary Doctor, we transform the 250 Lumpy Skin Disease images to making the dataset suitable for the algorithm used. This is done by cropping the area which is infected or symptoms occurred.

The cropped infected skin area we classified based on the help of veterinary doctor. And follow the following rules. The animals Lumpy Skin Disease were divided into three groups according to the severity of the clinical signs. In Severe stage animals developed ulcerative lesions on the muzzle and nostrils and numerous skin nodules over the entire body. In Mild stage manifested mild disease with fever and a few skin lesions. In early stage only transient fever but no other signs [18].

Than we got These 250 images datasets are separated into their corresponding three classes based on their characteristics. All the images are in JPEG (Joint Photographer Expert Group) file format.

The total number of images taken for this study, from each class; healthy skin, and Lumpy Skin Disease infected skin, are shown in Table 4.1 below

| No | Category | Number of collected image data | After Transformation | After Augment image |
|---|---|---|---|---|
| **1** | Normal skin | **120** | **150** | **580** |
| **2** | Mild Case Lumpy Skin Disease skin | **80** | **150** | **580** |
| **3** | Severe Case Lumpy Skin Disease skin | **50** | **150** | **580** |
| **Total** | | **250** | **450** | **1740** |

*Table 5-1 Number of images taken from each category*

Generally, the dataset contains 1392 train and 348 test images at the resolution of 200x200 color pixels from three different classes. In Figure 4.1, the representative images from this dataset are shown. Each class corresponds to Severe Lumpy Skin Disease Skin, Mild case Lumpy Skin Disease skin and Normal Skin respectively.

a) Severe Lumpy Skin Disease Skin b) Mild case Lumpy Skin Disease skin c) Normal skin

*Figure 5-1 representative images from this dataset, (a) Severe lumpy skin disease Skin, (b) Mild case Lumpy Skin Disease skin and (c) Normal skin*

## 5.4 Data augmentation

With the labelled original dataset, synthetic images can be created by various transformations to the original images [102]. Image Data Generators is one transformations method used for generating more training data from the original data to avoid model overfitting. There are various data augmentation techniques. The selected data augmentation techniques were: flipping images horizontally or vertically, rotating images at 40 degrees, rescaling outward or inward, randomly cropping, translating by width and height shifts, whitening, shearing, zooming and adding Gaussian noises to prevent model overfitting and enhance learning capability. Some example images generated by using the Image Data Generator are shown blow.

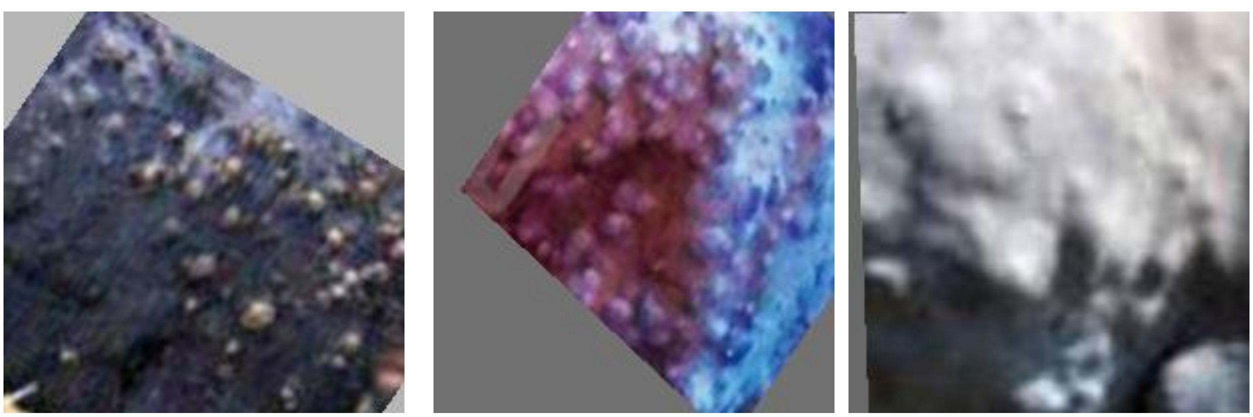


*Table 5-2 examples images generated by using the Image Data Generator*

## 5.5 Experimentation

In this experimentation section, we discuss the experiments carried out to implementation of the animal Lumpy Skin Disease detection system from filtering to classification. As described in chapter three, to increase the performance of the image we applied median filtering algorithm and from Adaptive thresholding, Edge-Based Segmentation and Otsu image segmentation methods we performed experiment to select the suitable segmentation algorithm. Based on expert suggestion we select the suitable algorithm. Finally, we classified preprocessed images by applying and without applying segmentation using constructed CNN model. For both experiment (applying and without applying segmented images) we test the performance of our model by using CNN for feature extraction and Softmax classifier for classification. In addition, we also test the performance of our model by applying CNN for feature extraction RF and SVM classifier for classification.

### 5.5.1 Experimenting filtering algorithm

Noise in images can make image unreadable perfectly and can cause inaccuracy in classification. Therefore, Noise removal is an important task in image processing. Image filtering is one of the key elements in image processing. In this study for smoothing image from noise we used median filtering and Gaussian filtering. The median filter and Gaussian filtering are very effective at removing impulse noise. The results of the experiment were evaluated by using peak signal –to-noise ratio (PSNR). This ratio is used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image. The average comparison result of PSNR of median filter and Gaussian filtering are 30.1 and 32.22 respectively. The result of filtering experiment show that Gaussian filtering algorithm produces better quality compared to median filtering.

(A) (B) (C)

*Figure 5-2 the comparison of original(A), Median filtering (B) and Gaussian filtering (C) filtered sever case LUMPY SKIN DISEASE cattle skin image*

### 5.5.2 Experimenting segmentation algorithms

Accurate segmentation of medical images is very important for the analysis and diagnosis of abnormalities in different parts of the body. For this work, we have done experiment by python programming code using Adaptive thresholding, Edge-Based Segmentation and Otsu image segmentation algorithms.

The result from the experimental are shown in the figure below for the input images of the Lumpy Skin Disease and the corresponding obtained output images obtained for the different Adaptive thresholding, Otsu method and Edge detection segmentation techniques.

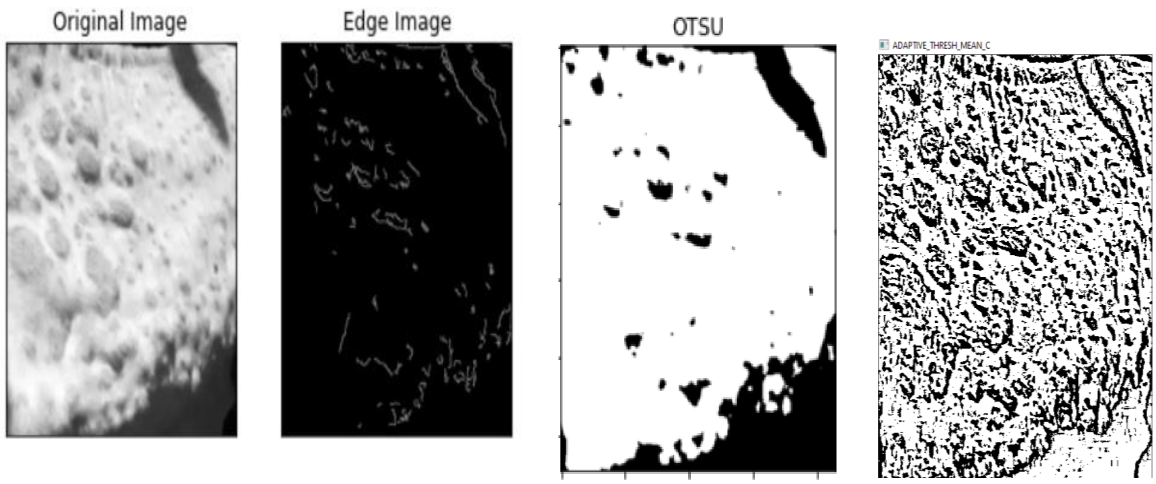



*Figure 5-3 Original input image (A), segmented image using edge detection (B), segmented image using OTSU segmentation (C), segmented image using Adaptive thresholding (D)*

During our experiments research, we main task is to answer which image segmentation applied in Lumpy Skin Disease Skin to shows good performance to be helpful for Lumpy Skin Disease recognition. The testing sample from actual images of Lumpy Skin Disease detection image.

We Applied edge detection, OTSU segmentation, Adaptive thresholding algorithms are compared with each other in objective way to give solution of Image Segmentation in Lumpy Skin Disease detection.

After we have applied edge detection, OTSU segmentation, Adaptive thresholding to segment all the sampling images, we invite the veterinary doctor to evaluate each segmented image according to subjective evaluation. the Adaptive thresholding segmentation method is better than OTSU segmentation and edge detection segmentation methods by comparison.

### 5.5.3 **Model Developments**

In our First experiment, we create CNNs model for extracting the feature from the image. The results from model used to the classifiers as inputs. We trained the first experiment without applying segmentation algorithm then employs SoftMax RF and SVM to classify the data obtained from the CNN-based feature extractor. In the second we trained the CNN model by applying segmentation algorithm to identify region of interest in the image for feature extraction and classify using SoftMax, RF and SVM classifiers.

### 5.5.4 Hyperparameter Tuning

From the total images 20% of train images are used as validation dataset for hyper-parameter selection is used. The optimizer and activation argument applied to CNN models. The optimizer Adam and activation argument sigmoid are selected.

### 5.5.5 Model construction

#### 5.5.5.1 LSDNet Model without applying segmentation

The first experiment is conducted using LSDNet Model. This classification algorithm is trained without applying segmentation algorithm to identify region of interest in the image. As clearly shown in figure 4.4 below, the LSDNet Model obtains training accuracy of 99.9 % and validation accuracy of 93.9%. These accuracies are obtained when the network is trained and tested without segmented image, and classified using Softmax classifier. validation accuracy is greater than training accuracy throughout training process, but at last epoch the difference become insignificant. Finally, the curve of validation accuracy is not stable up to final epochs.

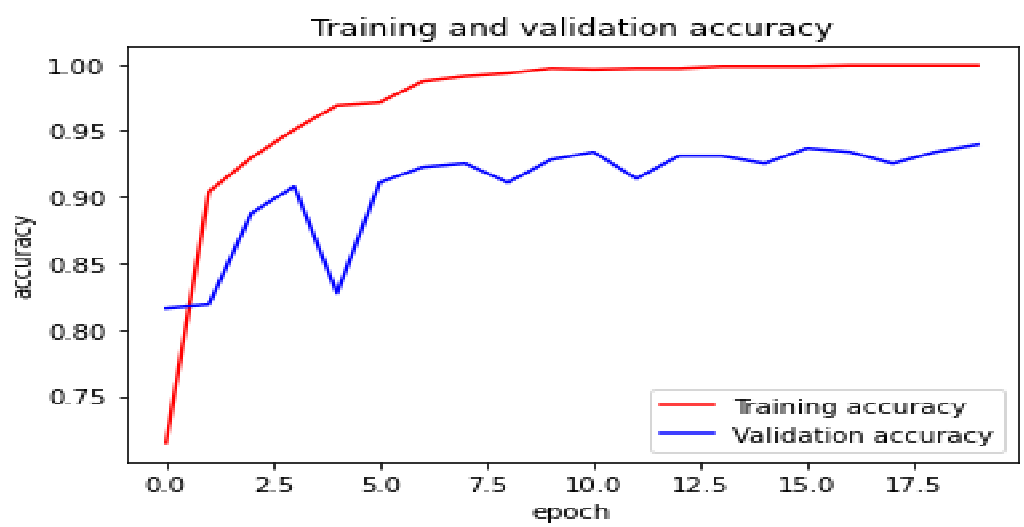



*Figure 5-4 Training and validation accuracy curve of LSDNet in training phase*

As clearly shown in figure 4.5 below training and validation loss are 0.018 and 0.13 respectively. It can clearly be seen that validation loss is not stable. On the other hand, training loss relatively more stable than validation loss. The training loss decrease from epoch 1 to 20. Finally, the curve of training and validation loss is not stable towards the final epochs.

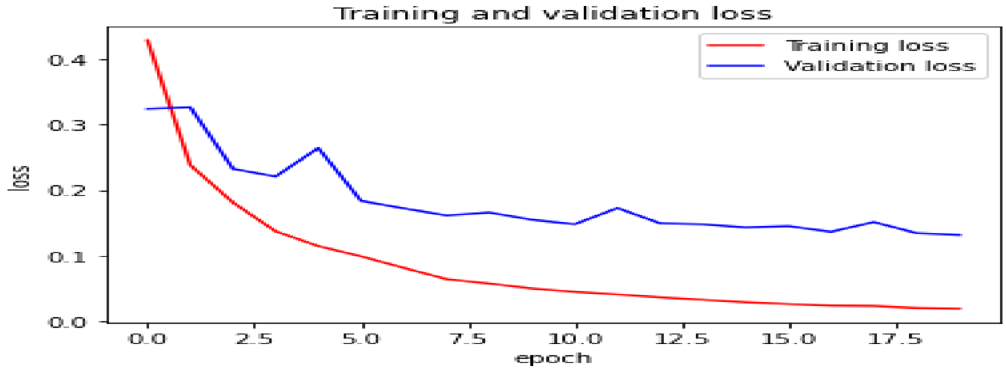



*Figure 5-5 Training and validation loss curve of LSDNet Model in training phase*

The performance of the LSDNet Model is also evaluated using different metrics, such as precision, recall and f1-score. Figure 4.6 shows how many of the images are misclassified and classified correctly. Table 5.6 below depict confusion matrix for each class.

```
[[112   4   0]
 [  4 112   0]
 [ 10   3 103]]
Out[17]: <AxesSubplot:>
```

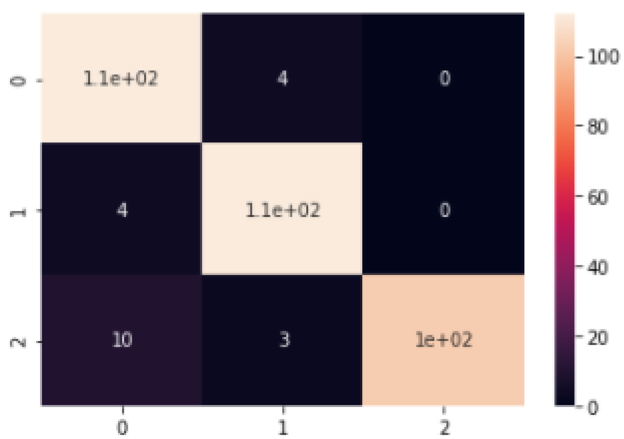



*Figure 5-6 confusion matrix for each class using sftmax classifier*

```
   Classification report using softmax classifier...
=================================================
                        precision    recall  f1-score   support

      Mild_case_rename       0.89      0.97      0.93       116
         Normal_rename       0.94      0.97      0.95       116
Severe_case_LSD_rename       1.00      0.89      0.94       116

              accuracy                           0.94       348
             macro avg       0.94      0.94      0.94       348
          weighted avg       0.94      0.94      0.94       348
```

*Figure 5-7 classification_report using softmax classifier*

Based on this experimental result, Normal skin out of the total, 96.5 % were correctly classified, but the rest 3.5% incorrectly classified as mild case. The Mild case skin out of the total, 96.5 % were correctly classified as Mild case, 3.5 % incorrectly classified as Normal Skin.  And sever skin out of the total, 8.6 % were incorrectly classified as mild case and 2.6 % as Normal skin but, 88.78 % are correctly classified.

.

### A. Comparison with Random Forest Classifier

We also conduct an experiment using LSDNet Model for feature extraction and RF and SVM for classification. The LSDNet Model with Random Forest obtains 89.6 % validation accuracy. This classification accuracy is obtained when the model is without segmented images. On the other side, the model designed using softmax classifier obtains 93.9 % classification accuracy. From this experiment that we observed using CNN as feature extractor and softmax as classifier has better classification accuracy than using CNN for feature extraction and RF classification.

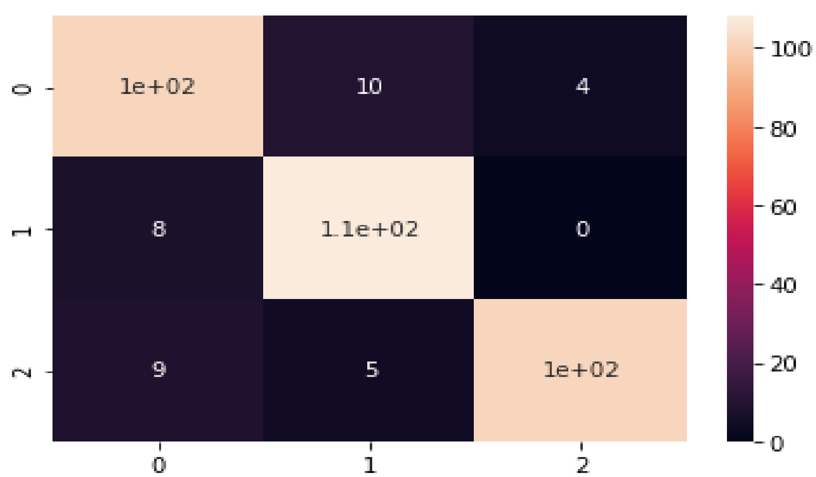



*Figure 5-8 confusion matrix for each class using RF classifier*

```
[[102  10   4]
 [  8 108   0]
 [  9   5 102]]

   Classification report using RF classifier...
==================================================
                        precision    recall  f1-score   support

      Mild_case_rename       0.86      0.88      0.87       116
         Normal_rename       0.88      0.93      0.90       116
Severe_case_LSD_rename       0.96      0.88      0.92       116

              accuracy                           0.90       348
             macro avg       0.90      0.90      0.90       348
          weighted avg       0.90      0.90      0.90       348
```

*Figure 5-9 classification report using RF classifier*

Experimental result of RF classifier, Normal skin out of the total, 93.1 % was correctly classified but 6.9 % incorrectly classified as mild case. the Mild case skin out of the total, 87.9 % were correctly classified as Mild case, 8.6% incorrectly classified as Normal Skin disease and 3.4 % incorrectly classified as severe case.  And sever skin out of the total, 93.1% are correctly classified, but 7.6 incorrectly classified as mild case and 4.3 % as Normal skin.

### B. Comparison with Random SVM

The LSDNet Model with SVM obtains 93.1 % validation accuracy. This classification accuracy is obtained when the model is without segmented images. On the other side, the model designed using softmax classifier obtains 93.9 % and using RF 89.6 % classification accuracy. From this experiment that we observed using CNN as feature extractor and softmax and SVM as classifier has equal accuracy value and better classification accuracy than using CNN for feature extraction and RF classification.

```
Out[75]: <AxesSubplot:>
```

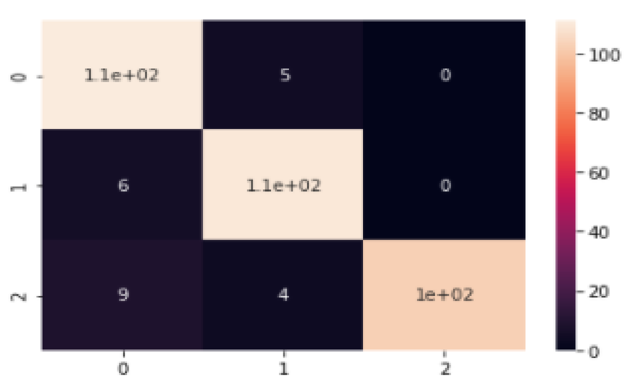



*Figure 5-10 **confusion matrix for each class using SVM classifier***

```
[[111   5   0]
 [  6 110   0]
 [  9   4 103]]

   Classification report using SVM classifier...
==================================================
                        precision    recall  f1-score   support

      Mild_case_rename       0.88      0.96      0.92       116
         Normal_rename       0.92      0.95      0.94       116
 Severe_case_LSD_rename       1.00      0.89      0.94       116

              accuracy                           0.93       348
             macro avg       0.94      0.93      0.93       348
          weighted avg       0.94      0.93      0.93       348
```

*Figure 5-11 classification report using SVM classifier*

Based on this experimental result, Normal skin out of the total, 94.8 % were correctly classified, but the rest 5.2% incorrectly classified as mild case. The Mild case skin out of the total, 95.7 % were correctly classified as Mild case, 4.3 % incorrectly classified as Normal Skin. And sever skin out of the total, 8.6 % were incorrectly classified as mild case and 2.6 % as Normal skin but, 88.8 % are correctly classified.

#### 5.5.5.2 LSDNet Model Model with applying segmentation

The second experiment is conducted using applying segmentation the images. From this experiment LSDNet Model is able to create a model with training accuracy of 100 % and validation accuracy of 94 % using Softmax classifier. The training and validation accuracy curve depicted in figure 4.8 below shows that, Training accuracy is increased up to epoch 3 and nearly linearly up to epoch 20 and reaches 100 % at last epoch 20, while validation accuracy generally is not stable increased oscillates up and down up to epoch 14 and reaches 94 % at last epoch.

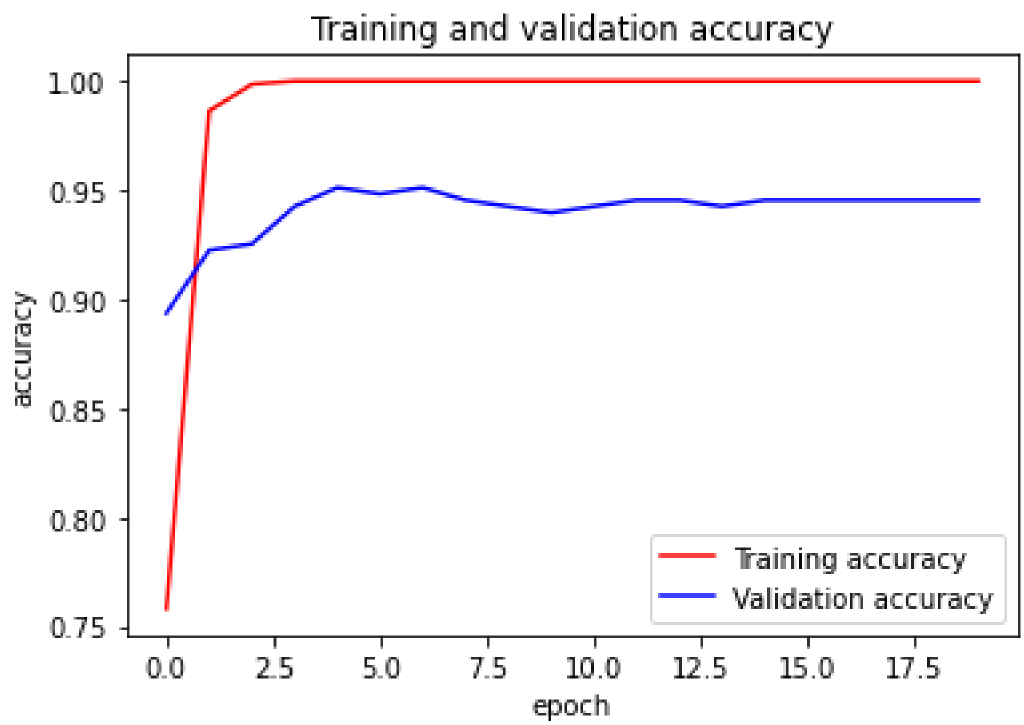



*Figure 5-12 Training and Validation loss*

In figure 4.12 below, initially training and validation loss was high. It can be clearly seen that; the validation accuracy decreases linearly up to epoch 3 and goes a lot of down and reaches the training lost 0.0018 at last epoch. While training loss also decreases intensely down up to epoch 3 and linearly reach 0.123 finally. The both training and validation loss are more stable than the previous experiment.

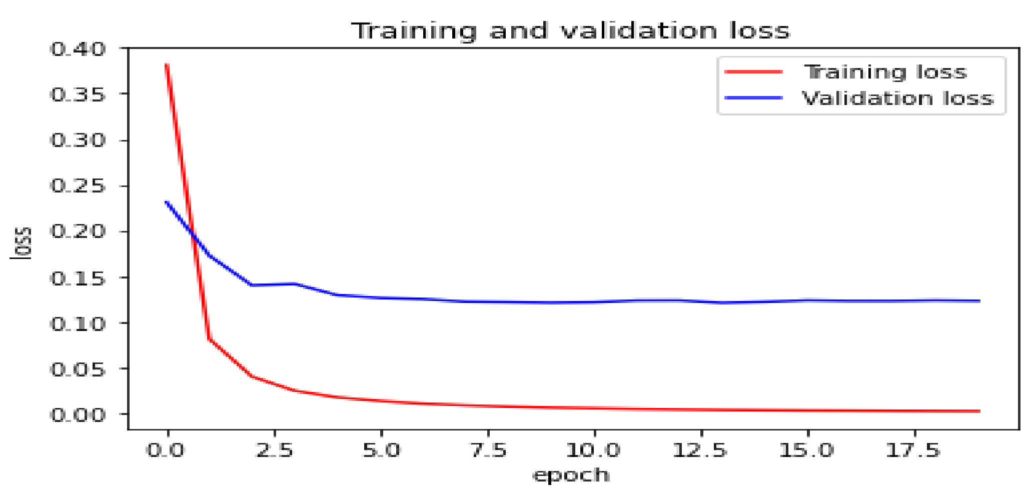



*Figure 5-13 Training and validation loss curve of LSDNet Model in training phase while applying segmentation*

We also evaluate the performance of our model using different metrics, such as precision, recall and f1-score. Table 4.3 below depict confusion matrix for each class. Classification using LSDNet Model achieves 94.8 % classification accuracy, 95% precision, 95% recall and 95% f1-score. Based on this experimental result, Normal skin out of the total, 94.8 % were correctly classified, but 4.3 % incorrectly classified as mild case and 0.86% incorrectly classified as severe. The Mild case skin out of the total, 93.9 % were correctly classified as Mild case, 3.4 % incorrectly classified as normal and 3.4 % incorrectly classified as Severe Lumpy Skin disease. And sever skin out of the total, 95.7 % are correctly classified, but 4.3% incorrectly classified as mild.

```
[[109   3   4]
 [  5 110   1]
 [  5   0 111]]
Out[17]: <AxesSubplot:>
```

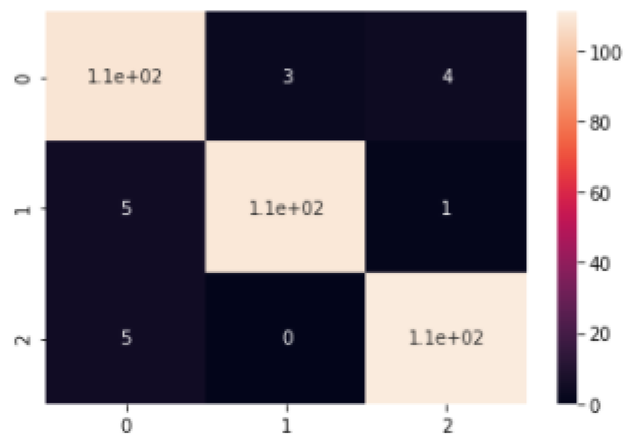



*Figure 5-14 confusion matrix for each class*

```
Classification report using softmax classifier...
=================================================
                       precision    recall  f1-score   support

     Mild_case_rename       0.91      0.94      0.92       116
        Normal_rename       0.97      0.97      0.97       116
Severe_case_LSD_rename       0.96      0.93      0.95       116

             accuracy                           0.95       348
            macro avg       0.95      0.95      0.95       348
         weighted avg       0.95      0.95      0.95       348
```

*Figure 5-15 classification report*

1. **Comparison with RF classifier**

We also conduct an experiment using CNN for feature extraction and RF for classification. in figure 4.10, the model constructed using RF classifier achieves classification accuracy, precision, recall and f1-score of 88%, 87% 87% and 87% respectively. This classification accuracy is obtained when the model is trained and tested with segmented images. On the other side, the model designed using softmax classifier obtains 94.8% classification accuracy, 95% precision, 95% recall and 95% f1-score. So those results clearly show using CNN as feature extractor and RF as classifier has less classification accuracy than using CNN for feature extraction and classification.

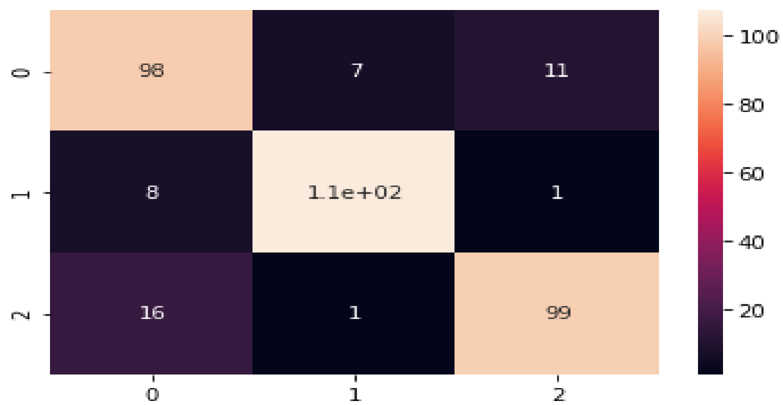



*Figure 5-16 confusion matrix for each class using RF classifier*

```
[[ 98   7  11]
 [  8 107   1]
 [ 16   1  99]]
Classification report using RF classifier...
=================================================
                     precision    recall  f1-score   support

      Mild_case_rename       0.80      0.84      0.82       116
         Normal_rename       0.93      0.92      0.93       116
Severe_case_LSD_rename       0.89      0.85      0.87       116

              accuracy                           0.87       348
             macro avg       0.88      0.87      0.87       348
          weighted avg       0.88      0.87      0.87       348
```

*Table 5-3 classification report*

Based on this experimental result, Normal skin out of the total, 92.2 % were correctly classified, but 6.9 % incorrectly classified as normal and 0.86 % as severe. the Mild case skin out of the total, 84.8 % were correctly classified as Mild case, 6 % incorrectly classified as Severe Lumpy

Skin disease and 9.2 % as normal.  And sever skin out of the total, 85.3 % are correctly classified but 13.8% incorrectly classified as mild case and 0.86% incorrectly classified as normal.

2. **Comparison with SVM classifier**

We also conduct an experiment using CNN for feature extraction and SVM for classification. in figure 4.10, the model constructed using RF classifier achieves classification accuracy, precision, recall and f1-score of 95.7 %, 96% 96% and 96% respectively. This classification accuracy is obtained when the model is trained and tested with segmented images. On the other side, the model designed using softmax classifier obtains 94.8% classification accuracy, 95% precision, 95% recall and 95% f1-score and using RF classifier obtains 87.4 % classification accuracy, 88% precision, 88% recall and 88% f1-score. So those results clearly show using CNN as feature extractor and RF as classifier has less classification accuracy than using CNN for feature extraction and SVM and softmax classification.

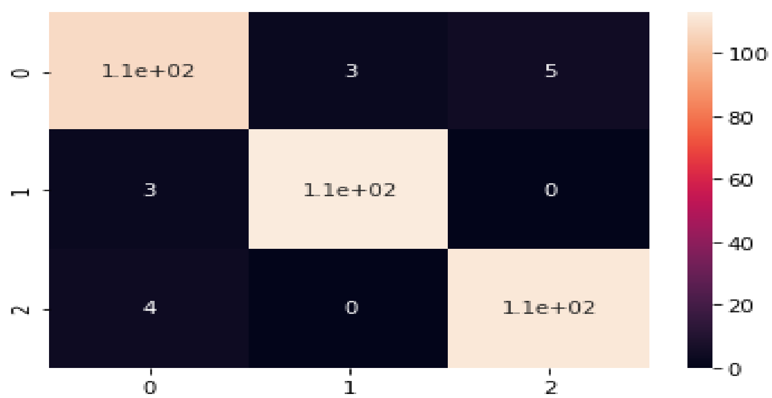



*Figure 5-17  confusion matrix for each class using SVM classifier*

```
[[108   3   5]
 [  3 113   0]
 [  4   0 112]]

   Classification report using SVM classifier...
=================================================
                        precision    recall  f1-score   support

      Mild_case_rename       0.94      0.93      0.94       116
         Normal_rename       0.97      0.97      0.97       116
Severe_case_LSD_rename       0.96      0.97      0.96       116

              accuracy                           0.96       348
             macro avg       0.96      0.96      0.96       348
          weighted avg       0.96      0.96      0.96       348
```

*Figure 5-18  classification report using svm*

Based on this experimental result, Normal skin out of the total, 93.1 % were correctly classified, but 2.6 % classified as mild case. The Mild case skin out of the total, 92.24 % were correctly classified as Mild case, 2.6 % incorrectly classified as normal and 4.31 % incorrectly classified as Severe Lumpy Skin disease.  And sever skin out of the total, 96.5 % are correctly classified, but the rest 3.5 % incorrectly classified as mild case.

## 5.6 Discussion of Results

In this study, in the first experiment we used preprocessed images without applying segmentation algorithm and we got training accuracy of 99.9 % and validation accuracy of 93.9%. The train accuracy for model is 7% higher than the test accuracy. The two loss curves are also separated. Images are misclassified incorrectly and the model have overfitting problem. For example, 9 severe images are incorrectly classified as normal skin. To overcame is problem and to increase the model detection accuracy we executed the second experiment by applying segmented images. We achieved training accuracy of 99.9 % and validation accuracy 95.7%. The train accuracy for model is 3.2 % higher than the test accuracy. The model overfitting problems have been improved significantly, but still exist in model. In this experiment Normal skin is not classified as severe and the severe image also is not classified as Normal. Severe Lumpy Disease is better detected than Mild Lumpy Skin Disease and Normal skin, and Normal skins are more detected than Mild case Lumpy Skin Disease. The misclassification of normal skin is because of scratch on the skin, as well as body loss of cattle, can lead to abnormal skin. The misclassification of mild lumpy skin disease as sever lumpy skin disease; because mild lumpy skin disease and sever lumpy skin disease have more similar symptoms which is sometimes difficult to distinguish distinctive feature among them. Because both have nodules on the skin but in mild case have a few skin lesions. Therefore, because of this misclassification occurs.

To summarize this study, during experimentation applying preprocessing and segmentation before feature extraction using CNN and classification using Softmax, RF and SVM classifiers have been classifying very well in animal lumpy skin disease detection. The results of the experiment detection result are described in Table 4.7 below.

Table 4. 3 Summary of Experiment Result

| No | Experiment | Feature extraction | Classification result using softmax | Classification result using RF | Classification result using SVM |
|---|---|---|---|---|---|
| 1 | Using LSDNet Model for Image Classification without applying segmentation | CNN | 93.9% | 89.6% | 93.9% |
| 2 | Using LSDNet Model for Image Classification with applying segmentation | CNN | 94.5% | 87.9 % | 95.7% |

*Table 5-4 Summary of the experiment result*

In General, as the best of researchers' knowledge, on the area of Lumpy Skin Disease detection no research work was done towards classification of Lumpy Skin Disease as sever and mild case and applying segmentation to increase an overall detection performance. In addition, there is no research work that use CNN for feature extraction and RF and SVM classifiers for classification to achieves better detection performance; this study is the first attempt by investigating the above two gaps.

# CHAPTER FIVE

# CONCLUSION AND RECOMMENDATION

## 6.1 Conclusion

Many research works are done so far in the area of human skin disease classification but only few studies conducted in animal skin disease classification. In this study, we developed a method to detect animal Lumpy Skin Disease and classify as Normal, Mild and Severe Lumpy Skin Disease skin diseases using image processing and machine learning algorithms. In this work we described an algorithm for animal Lumpy skin disease detection and classification. We used Convolutional Neural Network for feature extraction and SOFTMAX, RF and SVM classifier for classification.

This study involves data set preparation for training and testing Lumpy Skin Disease classification model. Dataset are preprocessed using Histogram equalization, Noise removal using Gaussian filter and segmented using Adaptive thresholding. This is followed by feature extraction using CNN. After extracted features from animal skin the classification model is built using Softmax, RF and SVM classifiers. The LSDNet model with image preprocessing and segmentation can improve the training accuracy to 100 % and validation accuracy to 95.7%. The superior model performance is further supported by confusion matrix.

In general, this study achieves better result towards detection of Lumpy skin disease and classify as Sever, Mild and Normal skin. The contribution of this study includes preparation of Lumpy skin disease Image dataset, construction of Lumpy skin disease Image classification model and Method to use local information to known incidence of animal Epidemic disease. The main challenge observed in this study is the non-existence of Lumpy skin disease Image data sate for experiment and Noises for properly detecting the region of interest.

## 6.2 Future Work

Based on the finding and investigations of the study, we recommend the following as a way forward.

- To experiment the proposed model in this study using larger dataset in order to validate the applicability of the model for real application
- The need to perform additional regularization tweaks and fine-tuning of hyperparameters so as to enhance the performance of the detection model.
- The need to apply advanced image preprocessing techniques to reduce the effect of noise in images
- To conduct an experiment using other feature extraction and classification techniques
- To conduct further studies on related skin diseases observed in animals
- To develop expert system based on the constructed detection model

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