SKIN DISEASE DETECTION USING DEEP LEARNING

A PROJECT REPORT

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DECLARATION

I undersigned hereby declare that the project report SKIN DISEASE DETECTION USING DEEP LEARNING, submitted for partial fulfillment of the requirements for the award of degree of Master of Computer Applications of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of Prof. Dr.Fousia M Shamsudeen. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

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C E R T I F I C A T E

This is to certify that, the project report entitled **"Skin Disease Detection Using Deep Learning"** is submitted by **VARSHA VISWANATH (TKM19MCA024)** to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the degree of Master of Computer Applications,is a bonafide record of the project work carried out by her under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

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ABSTRACT

Dermatological disorders are one of the most widespread diseases in the world. Despite being common its diagnosis is extremely difficult because of its complexities of skin tone, color, presence of hair. This paper provides an approach to use various computer vision based techniques (deep learning) to automatically predict the various kinds of skin diseases. The system consists of three phases- The feature extraction phase, the training phase and the testing / validation phase. The system makes use of deep learning technology to train itself with the various skin images. The main objective of this system is to achieve maximum accuracy of skin disease prediction. This work focuses on skin disease prediction using deep learning techniques. For the implementation, the dataset used for the skin disease prediction is the ISIC dataset with 8 category of skin diseases. For the classification, the deep learning algorithm used is ResNeT50. Restnet50 is a pretrained network, which can be used for the detection of skin disease detection using the concept of transfer learning. For that the neural network extracts image features from the skin images. The extracted features are used for disease detection for 8 classes of skin diseases.

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Chapter 1

INTRODUCTION

Skin is one in every of the most important and quickest developing tissues of the human body. It is a contamination that takes place in humans of all ages. Skin is regularly broken due to the fact it's far a touchy a part of the body. There are more than 3000 skin diseases. A cosmetically look spoiler disease will have a big effect and might reason extensive ache and everlasting injury. Most of the chronic skin conditions aren't right now deadly, they may be diagnosed as an extensive problem on fitness popularity which include physical, emotional and economic outcome. On the other hand, skin cancers are potentially lethal and their trouble is associated with the temporality that they carry. Now day's skin diseases become more common problem in human life. Most of these diseases are dangerous and harmful, particularly if not treated at an initial stage. People do not treat skin diseases seriously. Hence it is very important to control it at earlier stage to prevent it from spreading in people. It has become an important thing to treat these skin diseases properly at the earlier stages itself to prevent serious damage to skin. This system would help to solve this problem to a great extent. Since it system would allow users to determine the skin diseases to provide treatments or advice to patient by making use of images of skin infected with the disease and by obtaining information from the patient.

Skin diseases are quite difficult to identify and unpredictable. The use of smart phones and camera technology and utilize of image processing technology of the devices for skin diagnosis. Improvising machine learning based analytical tools are testing in improving and those are necessary to pick the right element and AI method to increase the accuracy. So, it is necessary to pick the right element and AI method to get more accuracy value. Machine-learning and image-processing dependent study and are applied in various areas such as fingerprint identification, face identification, tumour area recognition and for segmentation of effected area of skin disease. Deep learning algorithms are gaining prominence in skin disease classification.

To develop a purpose, we have two phases to solve a problem. The implementation phase con- sists of deep learning classifier. It is difficult to diagnose the skin disease in the primary stage and other stages because of the change in the characteristic features of the skin such as colour and tex- ture. This problem can be solving by using deep learning techniques on right selection of features to be determined for the analysis of skin disease samples. Deep learning is very effective tool for detecting and classifying the skin diseases. This tool is effective in verifying their results as it has pre-defined trained data set for classification. In this research, this system consists of 8 diseases, namely – actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, nevus, pigmented benign keratosis, squamous cell carcinoma and vascular lesion. In this paper, multiple factors are studied for potential improvement in the classification accuracy of skin diseases using deep transfer learning. Here, ResNet50 is used to for classification via transfer learning. Transfer learning generally refers to a process where a model trained on one problem is used in some way on a second related problem. In deep learning, transfer learning is a technique whereby a neural network model is first trained on a problem similar to the problem that is being solved. One or more layers from the trained model are then used in a new model trained on the problem of interest.

1.1 Problem Definition

The pattern of skin diseases varies due to environmental factors, hygienic standards, social customs, and genetics. Several skin illness have symptoms that can take a long time to treat since that can grow for months before being recognized, As a result, computer-based disease diagnosis comes into play since it can produce a result in a short period of time with more accuracy than human analysis utilizing laboratory procedures. Deep learning is the most widely used technology for skin disease predictions. Deep learning models will use inferred data to identify and explore features in unexposed data patterns, resulting in significant efficiently even with low computational models.

1.2 Objective

The main objective of this project is to automatically predict 8 different types of skin diseases using deep learning by analysing skin images with high accuracy and consistency.

- This system is proposed for the dissection of skin diseases using color images without the need for doctor intervention.
- Effectively recognize the disease.
- Deep learning algorithms that explicitly retrieve information and automatically extract features from the data using feature extraction techniques.
- The speed of the diagnosis process is increased, and human errors get minimized while employing these strategies.
- To enhance the classification accuracy and reduce error is performed using optimizing the weight parameters

Chapter 2

Related Works

Skin diseases are the 4th common cause of skin burden worldwide. Robust and Automated system have been developed to lessen this burden and to help the patients to conduct the early assessment of the skin lesion. Mostly this system available in the literature only provide skin cancer classification. Treatments for skin are more effective and less disfiguring when found early and it is a challenging research due to similar characteristics of skin diseases. In this project we attempt to detect skin diseases .A novel system is presented in this research work for the diagnosis of the most common skin lesions (Melanocytic nevi, Melanoma, Benign keratosis-like lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesion, Dermatofibroma). The proposed approach is based on the pre-processing, Deep learning algorithm, training the model , validation and classification phase. Experiments were performed on 10010 images and 97% accuracy is achieved for eight-class classification using Convolution Neural Networks (CNN) with the Keras Application API.

Noel C. F. Codella, David Gutman, M. Emre Celebi, Brian Helba, Michael A. Marchetti, Stephen W. Dusza, Aadi Kalloo, Konstantinos Liopyris, Nabin Mishra, Harald Kittler, Allan Halpern[1] proposed an image processing-based skin disease detection technique. They used the RGB image of the skin diseases area as input. Then resize the images and extract the features using a pre-trained convolution neural network model. They apply multi support vector machine for classification. They show that this method is simple, easy and the accuracy is 100%.

Philipp Tschandl, Cliff Rosendahl, Harald Kittler[2] show several studies of skin diseases in their review paper. All the studies are related to the classification of several skin diseases using the machine learning processes. They show a detailed review of the applied mechanisms, algorithms, and accuracies of those processes. In another review research article, R. Bhardwaj and S. Vatta [3] review different deep learning approaches for skin diseases detection. They briefly described different publicly available datasets, their image acquisitions process, and proposed algorithms.

In another research paper, Neetu Chikyal, K. Veera Swamy[4] used five different machine learning algorithms to detect skin diseases. They used random forest, kernel SVM, Naïve Bayes, Logistic Regression, and Convolution Neural Network algorithms. Finally from the confusion matrix, they discovered that the convolution neural network model gave the best result for this disease detection process.

A. Santy and R. Joseph [5] proposed an artificial intelligence system based on a neural network. This system has two parts first feature extraction, that was done by the image acquisition process. Second part was classification, which was done by the feed-forward neural network.

V. B. Kumar, S. S. Kumar and V. Saboo [6] proposed in their study six different data mining algorithms for classifying the different skin disease classes. The select 15 most salient features for predict the disease classes. Except for these six algorithms, the authors also create an ensem- ble method using Bagging, AdaBoost, and Gradient Boosting classifier techniques for prediction. Finally, they conclude the ensemble method provides a more accurate and effective prediction for skin disease detection.

R. Bhardwaj and S. Vatta [7] proposed an artificial intelligence system for skin cancer detection. They used image processing and a deep neural network for skin cancer detection. First, they segmented the affected area and extracted the features from the area using the image processing method, and for prediction, they used a convolution neural network. They achieved 93.7% for training accuracy and 89.5% for test accuracy.

Arifin, S., Kibria, G., Firoze, A., Amini, A., Yan, H [8] proposed another skin diseases detection model based on an adaptive federated machine learning process. This approach consists of intelligent local edges (dermoscopy) and a global point (server). This architecture can able to diagnosis the skin type, skin diseases type and also improve the accuracy constantly.

N. Hameed, A. M. Shabut and M. A. Hossain [9] the skin disease is detected by using color images without any supervision of dermatologist. This structure contains two stages, In the first stage the effected portion of skin is detected by using color image processing techniques, and active counter segmentation is used for segmentation to classify skin disease type and the second stage is to classify skin disease type by using different machine learning algorithms like artificial neural network, support machine vector, decision tree algorithms and so on. In artificial neural networks, the system was tested for five skin diseases type with accuracy of first phase 95.98% and the second phase has 94.02%.

In this research paper, P. R. Hegde, M. M. Shenoy and B. H. Shekar [10] the input images obtained from the user is processed to predict skin disease presence or absence from a new input image. The input image of a user would be obtained using android application. In this system, the application would ask the user with many questions and disease type is predicted using the end user answers. At last the proposed system, suggests medicinal descriptions, surgery and medicinal drug based on the skin disease trained model. Skin diseases like Eczema, Fungal infection and Urticaria are been analyzed in this project. This question and answer based application doesn’t provide promising results every time.

In another research paper, Zeljkovic, V., Druzgalski, C., Bojic-Minic, S., Tameze, C., Mayorga, P [11], Skin disease are mostly ignored and provided less importance at the early stages. Some ignorance among people might lead to skin cancer. In existing approach, the increased skin disease are identified at the later stage using biopsy only. The inspection is performed manually by considering many histopathological features. Thus this process is performed manually which can lead to human errors and takes 1-2 days for providing the biopsy results. Also the physician find it difficult to identify the type of skin disease and the stage of disease at the analysis stage. Thus making the medicine prescription difficult. This concern can be addressed by usage of machine learning and deep learning techniques by analyzing the microscope image. This proposed machine learning based approach can be an effective tool to identify the clinical data and provide the results in a short period of time. This approach can provide a promising results by combining computer vision and machine learning techniques.

This research paper, M. K. Rao, K. Veera Swamy and K. A. Sheela[12] predicts different types of skin diseases in which user can take the skin photo images and provide into the system which could process and provide variety of skin disease absence or presence. This proposed system used matlab tool for identifying different type if skin diseases like normal, melanoma, psoriasis or dermo case based on the extracted image features. This system would provide an alert to the nearby medical team if any abnormality is detected. This methodology suffers from the issues with segmentation issue thus making classification model less accuracy [12].

M T. Islam et al [13] proposed a deep convolutional neural network for skin disease detection to provide feasible and efficient system and due to the emergence of smart phones, image processing based disease analysis is more demandful as this could provide promising results in less time. Utilization of camera technique, the people can provide the input and integration of image processing and machine learning techniques the respective skin disease is identified and diagnosis is recommended. The input analysis are performed using two staged approach to address this problem. The first approach is the image processing technique and second approach is the machine learning technique to train the model. This trained model is kept on training to predict different types of skin diseases. As the characteristics and features of different skin disease are different, the machine algorithm needs to be trained for efficient prediction.

In this paper, R. Yasir, M. A. Rahman and N. Ahmed [14] proposed a model to use medical imaging to detect skin lesion in input skin images. They used methodology to create a prototype system to detect skin disease. The objective of this project is to identify skin lesion based on the input skin images texture analysis based on thresholding and neural network to detect and diagnose skin disease.

The work of Cristianini, N., Shawe, J [15] proposed the development of a Melanoma diagnosis tool for dark skin using specialized algorithm databases including images from a variety of Melanoma resources. Similarly, discussed classification of skin diseases such as Melanoma, Basal cell carcinoma (BCC), Nevus and Seborrheic keratosis (SK) by using the technique support vector machine (SVM). It yields the best accuracy from a range of other techniques. On the other hand, the spread of chronic skin diseases in different regions may lead to severe consequences. Therefore, [6] proposed a computer system that automatically detects eczema and determines its severity. The system consists of three stages, the first effective segmentation by detecting the skin, the second extract a set of features, namely color, texture, borders and third determine the severity of eczema using Support Vector Machine (SVM).

Yadav, S., Rathod, R., Pawar, S. R., Pawar, V. S., More, S [17] Composed of epidermis, der- mis, and subcutaneous tissues, skin is the largest organ of human body, containing blood vessels, lymphatic vessels, nerves, and muscles, which can perspire, perceive the external temperature, and protect the body. Covering the entire body, the skin can protect multiple tissues and organs in the body from external invasions including artificial skin damage, chemical damage, adventitious viruses, and individuals' immune system. Besides, skin can also avoid the loss of lipids together with water within epidermis and dermis so that skin barrier function can be stabilized.

In spite of defense and barrier function, skin is not indestructible in that skin tends to be constantly influenced by a variety of external and genetic factors. Currently, there are three main types of skin diseases appearing in human body, including viral skin diseases, fungal skin diseases, and allergic skin disease. Despite the fact that these types of skin diseases can be cured at present, these diseases indeed have brought trouble to patients' life. Nowadays, the majority of conclusions on the patients' existing symptoms are drawn mainly based on doctors' years of experience or their own subjective judgments, which may lead to misjudgments and consequently delay the treatment of these. therefore, it is of great theoretical significance and practical value to study how to extract symptoms of diverse skin diseases on the basis of modern science and technology. Under this circumstance, effective and accurate identification of the types of skin diseases can be achieved to prescribe treatment according to patients' symptoms.

Chapter 3

Skin Disease Detection

Introduction Skin lesions are a common disease that cause suffering, some of which can have serious consequences, for millions of people globally. Because of its complexity, diversity, and similarity, skin disease can only be diagnosed by dermatologists with long-term clinical experience and is rarely reproducible. It is likely to be misdiagnosed by an inexperienced dermatologist, which can exacerbate the condition and impede appropriate treatment. Thus, it is necessary to provide a quick and reliable method to assist patients and dermatologists in data processing and judgment.

Advances in deep learning have influenced numerous scientific and industrial fields and have realized significant achievements with inspiration from the human nervous system. With the rapid development of deep learning in biomedical data processing, numerous specialists have adopted this technique to acquire more precise and accurate data. With the rapid increase in the amount of available biomedical data including images, medical records, and omics, deep learning has achieved considerable success in a number of medical image processing problems. In this regard, deep learning is expected to influence the roles of image experts in biomedical diagnosis owing to its ability to perform quick and accurate assessments. This paper presents the characteristics of skin lesions, overviews image techniques, generalizes the developments in deep learning for skin disease classification, and discusses the limitations and direction of automatic diagnosis.

3.1 Challenges of Skin Disease Detection

Medicine is an area that is not yet fully understood. Information is not completely transparent. The characteristics of dermatology determine that the majority of the data cannot be obtained. At the same time, the AI technology route is immature, the identification accuracy of which must be improved owing to the uncertainty of manual diagnosis. There is no strict correspondence between the symptoms and results of a disease and no clear boundary between the different diseases. Thus, the use of deep learning for disease diagnosis continues to require considerable effort.

Before systematic debugging, extensive simulation, and robust validation, flawed algorithms could harm patients, which could lead to medical ethical issues, and therefore require forward-looking scrutiny and stricter regulation. As a “black box”, the principle of deep learning is unexplained at this stage, which could result in unpredictable system output. Moreover, it is possible that humans could not truly understand how a machine functions, even though it is actually inspired by humans.

There is a problem with the change in the error rate value in a data set, which is caused by the change in the size of the data set used in different skin cancer experiments. Therefore, the lack of a standard data set can lead to serious problems; the error rate values are considered in many experiments. In addition, the collection of datasets for numerous studies depends on individual research, leading to unnecessary effort and time. When the actual class is manually marked and compared to the predicted class to calculate one of the parameter matrices, pixels are lost when the background is cut from the skin cancer image using Adobe Photoshop. At this point, the process influences the results of all the parameter reliability groups (matrices, relationships, and behaviors), which are considered controversial. High reliability and low rate of time complexity cannot be achieved simultaneously, which is reflected in the training process and is influenced by conflicts between different standards, leading to considerable challenges.

Te data used for evaluation are frequently overly small to allow a convincing statement regard- ing a system’s performance to be made. Although it is not impossible to collect an abundance of relevant data through the Internet in this information age, this information, with significant uncertainty, apparently cannot meet the requirements of independent and identical distribution, which is one of the important prerequisites for deep learning to be successfully applied. For certain rare diseases and minorities, only a limited number of images are available for training. Numerous cases are required for the training process using deep learning techniques. In addition, although the deep learning technique has been successfully applied to other tasks, the developed models in skin are valid in only specific dedicated diseases and are not applicable to common situations.

3.2 Skin Disease Detection using Deep Learning

Deep learning has become an extremely popular method in recent years, and can be a powerful tool in complex, prior-knowledge-required areas, especially in the field of bio medicine, which is now facing the problem of inadequate medical resources. The application of deep learning in disease diagnosis has become a new research topic in dermatology. This paper aims to provide a quick review of the classification of skin disease using deep learning to summarize the characteristics of skin lesions and the status of image technology. We study the characteristics of skin disease and review the research on skin disease classification using deep learning. We analyze these studies using data sets, data processing, classification models, and evaluation criteria. We summarize the development of this field, illustrate the key steps and influencing factors of dermatological diagnosis, and identify the challenges and opportunities at this stage. Our research confirms that a skin disease recognition method based on deep learning can be superior to professional dermatologists in specific scenarios and has broad research prospects.

Using the deep learning technique, the pattern recognition of images can be performed automatically once the program is established. Images can be input to a CNN with high fidelity and important features can be automatically obtained. Therefore, information extraction from images prior to the learning process is not necessary with this technique. In shallow layers, simple features such as the edges within the images are learned. At deep layers near the output layer, more complex high-order features are learned. Different researchers, institutions, and challenges are working on the automatic diagnosis of skin disease, and different deep learning methods have been developed for the recognition of dermatological disease; these have been proven to be effective in numer-

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ous fields. For example, the International Skin Imaging Collaboration (ISIC) is a challenge that focuses on the automatic analysis of skin lesions. The goal of the challenge (started in 2017) is to support the research and development of algorithms for the automated diagnosis of melanoma including lesion segmentation, dermoscopic feature detection within a lesion, and classification of melanoma, which is also the main goal in the field of dermatology. In general, this method is a modeling framework that can learn the functional mapping from the input images to output. The input image is a preprocessed image; the output image is a segmentation mask. The network structure involves a series of convolution and pooling layers, followed by a fully connected layer, followed by a series of unpooling and disconnection operations

Chapter 4

METHODOLOGY

In this section, the methodology of the proposed system for detection, extraction and classification of skin diseases images is described. The system will help significantly in the detection of actinic keratosis, basal cell carcinoma, dermatofibroma, melanoma, naevus, pigmented benign keratosis, seborrheic keratosis, squamous cell carcinoma, vascular lesion. The whole architecture can be divided into several modules comprising of preprocessing, feature extraction, and classification.

Actinic Keratosis: A rough, scaly patch on the skin that develops from years of sun exposure. It's often found on the face, lips, ears, forearms, scalp, neck or back of the hands..

Basal cell carcinoma: Type of skin cancer that most often develops on areas of skin exposed to the sun, such as the face. On brown and Black skin, basal cell carcinoma often looks like a bump that's brown or glossy black and has a rolled border. Basal cell carcinoma is a type of skin cancer.

Dermatofibroma: A common cutaneous nodule of unknown etiology that occurs more often in women. Dermatofibroma frequently develops on the extremities (mostly the lower legs) and is usually asymptomatic, although pruritus and tenderness can be present.

Melanoma:A form of skin cancer that begins in the cells (melanocytes) that control the pigment in your skin. This illustration shows melanoma cells extending from the surface of the skin into the deeper skin layers.

Naevus: A nonspecific medical term for a visible, circumscribed, chronic lesion of the skin or mucosa. The term originates from nævus, which is Latin for ”birthmark”; however, a nevus can be either congenital (present at birth) or acquired.

Pigmented Benign Keratosis:A seborrheic keratosis (seb-o-REE-ik ker-uh-TOE-sis) is a common noncancerous (benign) skin growth. People tend to get more of them as they get older. Seborrheic keratoses are usually brown, black or light tan. The growths (lesions) look waxy or scaly and slightly raised.

Seborrheic Keratosis:A common noncancerous (benign) skin growth. People tend to get more of them as they get older. Seborrheic keratoses are usually brown, black or light tan. The growths (lesions) look waxy or scaly and slightly raised.

Vascular Lesion: Vascular lesions are relatively common abnormalities of the skin and underlying tissues, more commonly known as birthmarks. There are three major categories of vascular lesions: Hemangiomas, Vascular Malformations, and Pyogenic Granulomas.

4.1 Dataset

https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000, a collection of multi-source dermatoscopic images. Deep learning requires a large number of images to extract disease features. These datasets are typically available from the Internet, open dermatology databases, and hospitals in collaboration with research units, and are labeled by professional dermatologists after removing blurry and distant images. An excellent dataset should be composed of dermoscopic images. Dermoscopy is a noninvasive skin imaging technology that can observe the skin structure at the junction of the epidermis and dermis, and clearly indicate the nature, distribution, arrangement, edge, and shape of pigmented skin lesions. Because of the uncertainty of imaging conditions, such as shooting angle, illumination, and storage pixels, the imaging effect of non-dermoscopic images can be influenced.

For the experimental purpose here various skin disease datasets are used. All the datasets are collected from Kaggle. The final dataset contains more than forty thousand images of skin disease data. All the images are divided into 8 skin disease classes.The database is split into; training set, validating/testing set. A training set is adopted for learning to fit the parameters and is specifically applied to alter the varying weights and errors of the system in each training run. Validation/testing set tunes the parameters and is used only to assess the effectiveness and efficiency of the system. In this method, the divide mode is set to 80% for the training of the data, 20% for the validating/testing of the data.

4.2 Data Collection and Pre-processing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. The aim of pre-processing is an improvement of the data for further processing. Pre-processing of data is carried out before model is built and training process is executed. Effective image quality can improve the generalization ability of a model. Preprocessing can reduce irrelevant information in the image, improve the intensity of the relevant information, simplify the data, and improve the reliability. Te general image preprocessing process is as follows:

Image segmentation: Skin lesion segmentation is the essential step for the majority of classification tasks. Accurate segmentation contributes to the accuracy, computation time, and error rate of subsequent lesion classification. It is crucial for image analysis for the following two reasons. First, the border of a lesion provides important information for accurate diagnosis, including numerous clinical features such as asymmetry and border irregularity. Secondly, the extraction of other important clinical features such as atypical dots and color variegation critically depends on the accuracy of the border detection. Given a inputted dermoscopic image, the goal of the segmentation process is to generate a two-dimensional mask that provides an accurate separation between the lesion area and surrounding healthy skin.

Resize: Lesions frequently occupy a relatively small area, although skin images can be considerably large. Before this task, images for a deep learning network should be preprocessed because the resolution of the original lesion images is typically overly large, which entails a high computation cost. Accurate skin lesion segmentation enhances its capability by incorporating a multiscale contextual information integration scheme. To avoid distorting the shape of the skin lesion, the images should be cropped to the center area first and then proportionally resized. Images are frequently resized to 224×224 or 227×227 pixels through scaling and clipping, which is the appropriate size after combining the amount of calculation and information density.

Normalization: Te image data are mapped to the interval of [0,1] or [1,1] in the same dimen- sion. Te essence of normalization is a kind of linear transformation that does not cause “failure” after changing the data. Conversely, it can improve the performance of the data, accelerate the solution speed of gradient descent, and enhance the convergence speed of the model.

Data augmentation: Owing to privacy and professional equipment problems, it is difficult to collect sufficient data in the process of skin disease identification. A data set that is overly small can easily lead to overfitting owing to the lack of learning ability of the model, which makes the network model lack generalization ability. A method called data augmentation is adopted to expand the dataset to meet the requirements of deep learning for big data, such as rotation, random cropping, and noise.

4.3 Feature Extraction

Early detection of lesions is a crucial step in the field of skin cancer treatment. There is a significant benefit if this can be achieved without penetrating the body. Feature extraction of skin disease is an important tool that can be used to properly analyze and explore an image. Feature extraction can be simply viewed as a dimensionality reduction process; that is, converting picture data into a vector of a certain dimension with picture features. Before deep learning, this was typically determined manually by dermatologists or researchers after investigating a large number of digital skin lesion images. A well-known method for feature extraction is based on the ABCD rule of dermoscopy. ABCD stands for asymmetry, border structure, color variation, and lesion diameter. It defines the basis for disease diagnosis. Te extracted and fused traits such as color, texture, and Histogram of Oriented Gradient (HOG) are applied subsequently with a serial-based method. Te fused features are selected afterwards by implementing a novel Boltzman entropy method, which can be used for the early detection. However, this typically has enormous randomness and depends on the quantity and quality of the pictures, as well as the experience of the dermatologists.

4.4 Classification

From a classifcation perspective, feature extraction has numerous benefits:

- reducing classifier complexity for better generalization
- improving prediction accuracy
- reducing training and testing time
- enhancing the understanding and visualization of the data

. The mechanism of neural networks is considerably different from that of traditional methods. Visualization indicates that the first layers are essentially calculating edge gradients and other simple operations such as SIFT and HOG. Te folded layers combine the local patterns into a more global pattern, ultimately resulting in a more powerful feature extractor. In a study using nearly 130000 clinical dermatology images, 21 certified dermatologists tested the skin lesion classification with a single CNN, directly using pixels and image labels for end-to-end training; this had an accuracy of 0.96 for carcinoma. Subsequently, researchers used deep learning to develop an automated classification system for 8 skin disorders by learning the abnormal characteristics of a malignancy and determined visual explanations from the deep network. A third study combined deep learning with traditional methods such as hand-coded feature extraction and sparse coding to create a collection for melanoma detection that could yield higher performance than expert dermatologists. These results and others confirm that deep learning has significant potential to reduce doctors' repetitive work.

4.5 Evaluation

Evaluation and criterion, typically based on the following three points, reliability, time consumption, and training and validation are vital in this field. Researchers have used all three criteria to develop and design methods and techniques for detecting and diagnosing skin disease. Others have used only two criteria, reliability, and training and validation to evaluate and discuss the different types of classifiers. Numerous studies have demonstrated that acceptable reliability, time complexity, and error rates within a dataset cannot be achieved at the same time; hence, researchers must establish different standards. Once one of them is selected, the performance of the others diminishes. Consequently, conflicts among dermatological evaluation criteria pose a serious challenge to dermatological classification methods. These requirements must be considered during the evaluation and benchmarking. Te dermatological classification method should standardize the requirements and objectives and use a programmatic process in research, evaluation, and benchmarking. Moreover, new flexible evaluations should address all conflicting standards and issues.

Despite the conflicts, important criteria are the key goals for evaluation and benchmarking. It is necessary to develop appropriate procedures for these goals while increasing the importance of specific evaluation criteria and decreasing other standards. When evaluating the results obtained using the diagnostic model, researchers must consider the quality of the dataset used to build the model and choose the parameters that can adjust that model. Te time complexity and error rate in the dataset have proven to be important in the field of dermatology, which, with more consideration during the evaluation process, can optimize the consistency of the results. In general, the goal is to obtain a balanced classifier for sensitivity and specificity

4.6 CNN Architecture

Convolutional Neural Network (CNN) is a development of the Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN is included in the type of Deep Neural Network because it has a high network depth and has been widely applied to image data. CNN has an architecture as like as neural networks in general, neurons in CNN have a weight, bias, and activation function. CNN architecture as shown in Figure 4.2, which consists of the convolution layer with ReLU activation, pooling layer as feature extraction layer, and fully connected layer with softmax activation as classification layer.

In the Convolution layer, the convolution process is the main process that underlies CNN. Convolution layer is the first layer that will process the image as an input system model. The image will be convoluted with a filter to extract features from the input image that is called the feature map.The Convolutional neural network consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions. This product is usually the Frobenius inner product, and its activation function is commonly ReLU. As the convolution kernel slides along the input matrix for the layer, the convolution operation generates a feature map, which in turn contributes to the input of the next layer. This is followed by other layers such as pooling layers, fully connected layers, and normalization layers. Convolutional layers convolve the input and pass its result to the next layer. Pooling layers reduce the dimensions of data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer. Fully connected layers connect every neuron in one layer to every neuron in another layer.

4.7 RESNET 50 Architecture

Since Convolutional neural networks have proved very effective in representation learning, as they extract features through convolutional filters and train the parameters through backpropagation, we use a state-of-the art convolutional neural network, ResNet50, pretrained on the ImageNet dataset. The image are resized to 224x224 to fit the input requirements of the ResNet50. The features are obtained by removing the last fully connected layer to get the 2048 dimensional feature vector. These feature vectors were obtained easily without the use of much computational power. Since ResNet50 has the capability to provide effective feature for most images we did not finetune it according to our dataset and instead used the pretrained weights from the ImageNet dataset. ResNet50 is a variant of ResNet model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8 x $10\hat{9}$ Floating points operations. It is a widely used ResNet model and we have explored ResNet50 architecture in depth.There was a small change that was made for the ResNet 50 and above that before this the shortcut connections skipped two layers but now they skip three layers and also there was 1 * 1 convolution layers added that we are going to see in detail with the ResNet 50 Architecture.

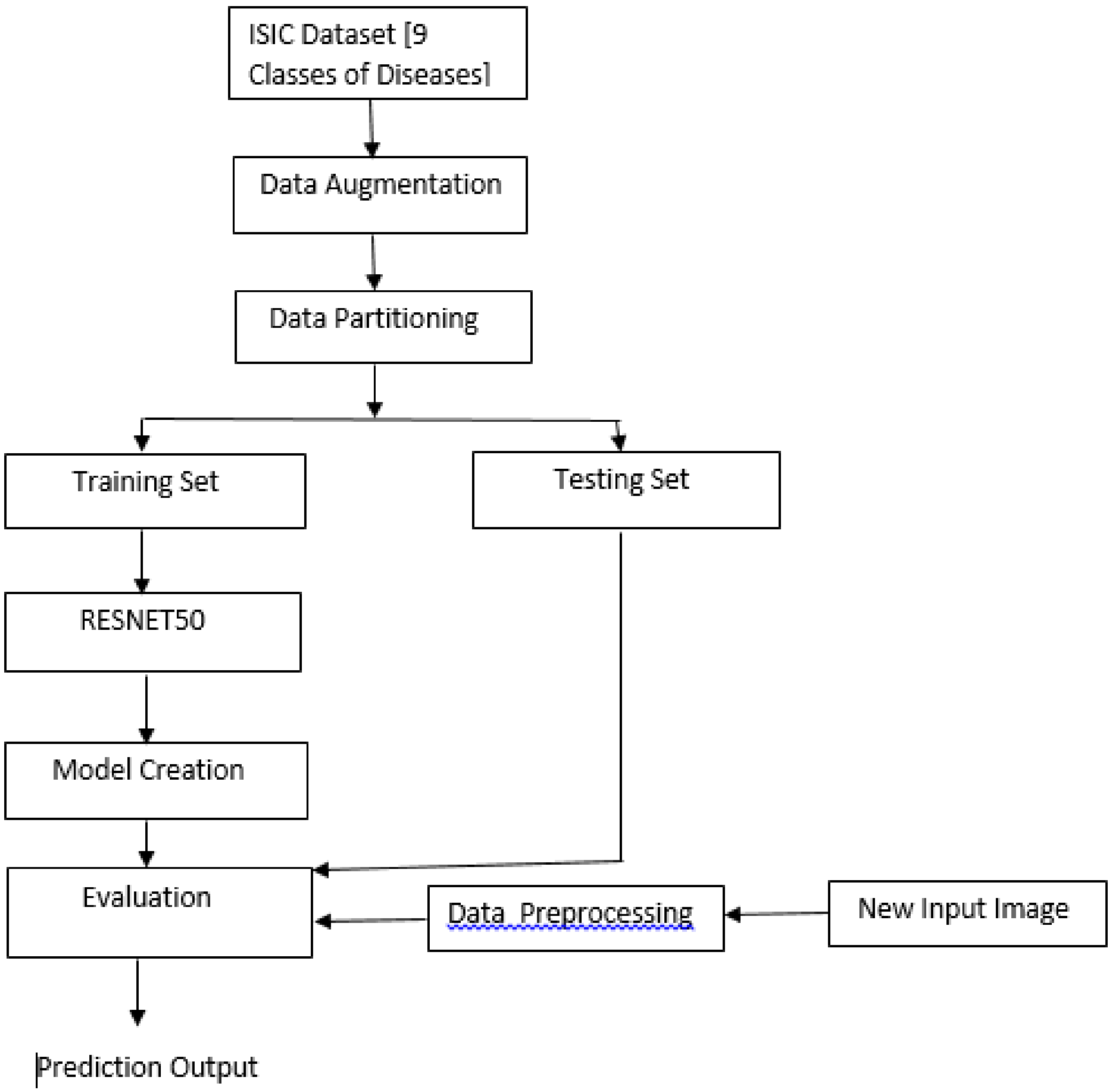

Figure 4.1: System Architecture

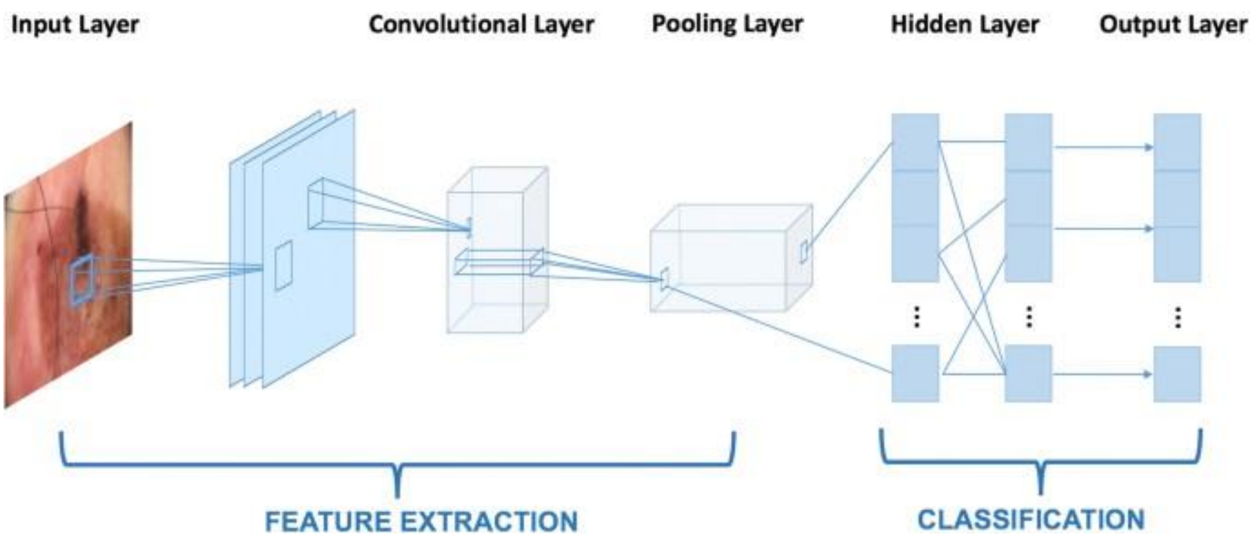

Figure 4.2: Architecture of CNN

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 4.3: Architecture of RESNET 50

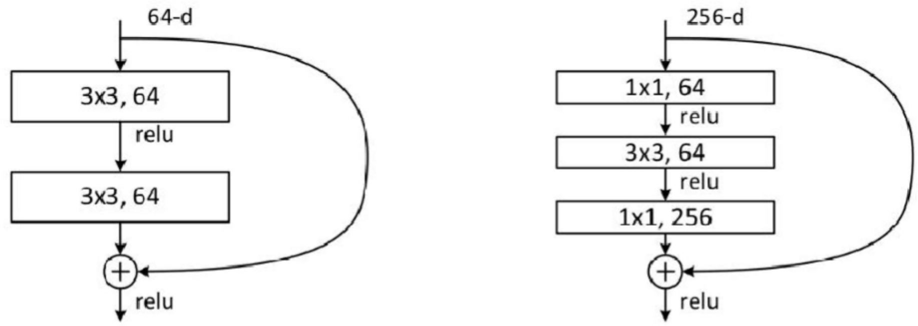

Figure 4.4: Skip Connections

Chapter 5

Experimental setup and Results

5.1 Software Requirements

The software used for the project:

• Python

• Anaconda

• MySql

• Django

5.1.1 Python

Python is an object-oriented programming language created by Guido Rossum in 1989. It's ideally designed for fast prototyping of complicated applications. It has interfaces to several OS system calls and libraries and is protractile to C or C++. several massive corporations use the Python programming language embody NASA, Google, YouTube, BitTorrent, etc. Python programming is widely utilized in AI, natural language Generation, Neural Networks and other advanced fields of computer science. Python is programming language open supply, high-level artificial language developed by Guido van Rossum within the late Eighties and presently administered by Python Software Foundation. It came from the ABC language that he helped produce early on in his career. Python is a powerful language that you can use develop games, write GUIs, and develop web applications. It's a high-level language. Reading and writing codes in Python is far like reading and writing regular English statements. As a result, they're not written in the machine-readable language, Python programs got to be processed before machines can run them. Python is an understood language. This implies that each time a program is run, its interpreter runs through the code and interprets it into machine-readable byte code. Python is an object-oriented language control users to manage and management data structures or objects to make and run programs. Everything in Python is, in fact, top-notch. All objects, data types, functions, methods, and classes take an equal position in Python. Programming languages are created to satisfy the requirements of programmers and users for an efficient tool to develop applications that impact lives, lifestyles, economy, and society. they assist build lives better by increasing productivity, enhancing communication, and rising potency. Languages die and become obsolete once they fail to live up to expectations and are replaced and superseded by languages that are more powerful. Python programming language artificial language that has stood the test of time and has remained relevant across industries and businesses and among programmers, and individual users. It's a living, thriving, and extremely helpful language that's extremely recommended as a primary programming language for those that want to dive into and experience programming.

5.1.2 Anaconda

Anaconda is a free and open-source distribution of the Python and R programming languages for scientific computing (data science, machine learning applications, large-scale data processing, predictive analytics, etc.), that aims to simplify package management and deployment. Package versions are managed by the package management system conda. The Anaconda distribution includes data-science packages suitable for Windows, Linux, and MacOS. Anaconda distribution comes with more than 1,500 packages as well as the conda package and virtual environment manager. It also includes a GUI, Anaconda Navigator], as a graphical alternative to the command line interface (CLI). Big difference between conda and the pip package manager is in how package dependencies are managed, which is a significant challenge for Python data science and the reason conda exists. When pip installs a package, it automatically installs any dependent Python packages without checking if these conflict with previously installed packages. It will install a package and any of its dependencies regardless of the state of the existing installation. Because of this, a user with a working installation of, for example, Google Tensorflow, can find that it stops working having used pip to install a different package that requires a different version of the dependent numpy library than the one used by Tensorflow.

In some cases, the package may appear to work but produce different results in detail.In contrast, conda analyses the current environment including everything currently installed, and, together with any version limitations specified, works out how to install a compatible set of dependencies, warning if this cannot be done.Open source packages can be individually installed from the Anaconda repository, Anaconda Cloud (anaconda.org), or your own private repository or mirror, using the conda install command. Anaconda Inc compiles and builds all the packages in the Anaconda repository itself, and provides binaries for Windows 32/64 bit, Linux 64 bit and MacOS 64-bit. Anything available on PyPI may be installed into a conda environment using pip, and conda will keep track of what it has installed itself and what pip has installed.Custom packages can be made using the conda build command, and can be shared with others by uploading them to Anaconda Cloud,PyPI or other repositories.The default installation of Anaconda2 includes Python 2.7 and Anaconda3 includes Python 3.7. However, it is possible to create new environments that include any version of Python packaged with conda. Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda distribution that allows users to launch applications and manage conda packages, environments and channels without using command-line commands. Navigator can search for packages on Anaconda Cloud or in a local Anaconda Repository, install them in an environment, run the packages and update them.

5.1.3 Django

A high-level Web framework is software that eases the pain of building dynamic Web sites. It abstracts common problems of Web development and provides shortcuts for frequent programming tasks. For clarity, a dynamic Web site is one in which pages aren't simply HTML documents sitting on a server's file system somewhere. In a dynamic Web site, rather, each page is generated by a computer program — a so-called "Web application" — that you, the Web developer, create. A Web application may, for instance, retrieve records from a database or take some action based on user input.

It provides a method of mapping requested URLs to code that handles requests: It gives you a way of designating which code should execute for which URL. For instance, you could tell the framework, “For URLs that look like /users/joe/, execute code that displays the profile for the user with that username.”

It makes it easy to display, validate and redisplay HTML forms: HTML forms are the primary way of getting input data from Web users, so a Web framework had better make it easy to display them and handle the tedious code of form display and redisplay (with errors highlighted).

It converts user-submitted input into data structures that can be manipulated conveniently: The framework could convert HTML form submissions into native data types of the programming language you’re using.

It helps separate content from presentation via a template system, so you can change your site’s look-and-feel without affecting your content, and vice-versa.

It conveniently integrates with storage layers, such as databases — but doesn’t strictly require the use of a database.

It lets you work more productively, at a higher level of abstraction, than if you were coding against, say, HTTP. But it doesn’t restrict you from going “down” one level of abstraction when needed.

It gets out of your way, neglecting to leave dirty stains on your application such as URLs that contain “.aspx” or “.php”.

The framework is written in Python, a beautiful, concise, powerful, high-level programming language. To develop a site using Django, you write Python code that uses the Django libraries. Although this book doesn’t include a full Python tutorial, it highlights Python features and functionality where appropriate, particularly when code doesn’t immediately make sense and that encourages rapid development.

5.1.4 MySql

Its name is a combination of ”My”, the name of co-founder Michael Widenius’s daughter, and ”SQL”, the abbreviation for Structured Query LanguageA database is a separate application that stores a collection of data. Each database has one or more distinct APIs for creating, accessing, managing, searching and replicating the data it holds.

Other kinds of data stores can also be used, such as files on the file system or large hash tables in memory but data fetching and writing would not be so fast and easy with those type of systems. Nowadays, we use relational database management systems (RDBMS) to store and manage huge volume of data. This is called relational database because all the data is stored into different tables and relations are established using primary keys or other keys known as Foreign Keys. MySQL is the most popular Open Source Relational SQL database management system. MySQL is one of the best RDBMS being used for developing web-based software applications. MySQL is a fast, easy-to-use RDBMS being used for many small and big businesses. MySQL is developed, marketed and supported by MySQL AB, which is a Swedish company. MySQL is becoming so popular because of many good reasons-

- MySQL is released under an open-source license. So you have nothing to pay to use it.
- MySQL is released under an open-source license. So you have nothing to pay to use it.
- MySQL uses a standard form of the well-known SQL data language.
- MySQL works on many operating systems and with many languages including PHP, PERL, C, C++, JAVA, etc.
- MySQL works very quickly and works well even with large data sets.
- MySQL is very friendly to PHP, the most appreciated language for web development
- MySQL supports large databases, up to 50 million rows or more in a table. The default file size limit for a table is 4GB, but you can increase this (if your operating system can handle it) to a theoretical limit of 8 million terabytes (TB).
- MySQL is customizable. The open-source GPL license allows programmers to modify the MySQL software to fit their own specific environments.

5.2 Training and Validation results

The model is trained for 5 epochs, with a batch size if 64,which amounts to 6000 steps per epoch for training and a batch size of 64 was employed for the testing phase which contributes towards 39 steps per epoch for testing. Thus, training for 5 such epochs yielded optimized results, with high accuracy of 97% for CNN and 94% for RESNET 50 and corresponding loss of 0.08%, 0.15% respectively for training. For CNN and RESNET 50 its, 97.63 % and 93.65% accuracy respectively for validation. The given table 5.1 shows both models training and testing accuracy.

```
[6]  ▷ M↓
     model.fit(x_train, y_train, epochs=5)

     Train on 60000 samples
     Epoch 1/5
     60000/60000 [==============================] - 4s 68us/sample - loss: 0.2991 - accuracy: 0.9123
     Epoch 2/5
     60000/60000 [==============================] - 3s 52us/sample - loss: 0.1463 - accuracy: 0.9563
     Epoch 3/5
     60000/60000 [==============================] - 3s 53us/sample - loss: 0.1081 - accuracy: 0.9667
     Epoch 4/5
     60000/60000 [==============================] - 3s 54us/sample - loss: 0.0885 - accuracy: 0.9733
     Epoch 5/5
     60000/60000 [==============================] - 3s 55us/sample - loss: 0.0744 - accuracy: 0.9763

     <tensorflow.python.keras.callbacks.History at 0x292692d40c8>
```

Table 5.1: Accuracy after Training

5.3 Performance metrics for validation phase

Model evaluation metrics are required to quantify model performance. The choice of evaluation metrics depends on a given machine learning task such as classification, regression, ranking, clustering, topic modeling, among others.

Accuracy (ACC) is calculated as the number of all correct predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

$$Precision = TP/(TP + FP) \tag{5.1}$$

Recall is also one of the most common performance metrics to estimate the performance of the classification model. The recall is the fraction of the total amount of relevant instances that were actually the retrieved instance of the classification algorithm.

$$Recall = TP/(TP+TN) \tag{5.2}$$

In statistical analysis of binary classification the f1 score is a measure for testing accuracy. It considers both the precision and the recall of the classification algorithm to compute the f1 score.

$$F1score = precision * Recall/(precision + Recall) \tag{5.3}$$

The outcomes of the most common performance matrix such as classification accuracy,precision,recall and f1 score shows that proposed RESNET 50 gives a better performance than CNN. Performance metrics of RESNET 50 models is shown in table 5.2

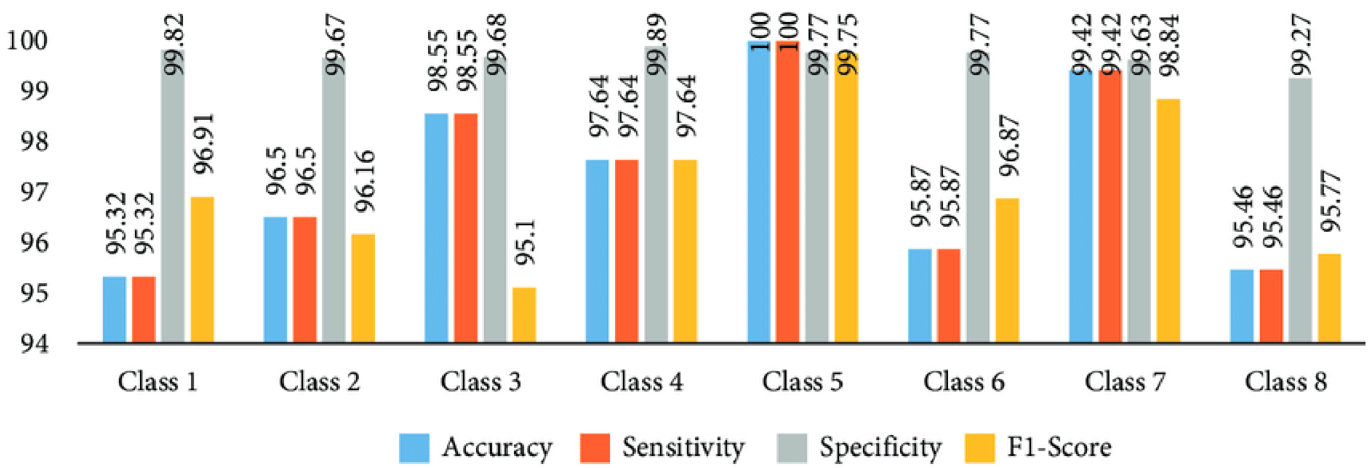

Table 5.2: Performance metrics of RESNET 50

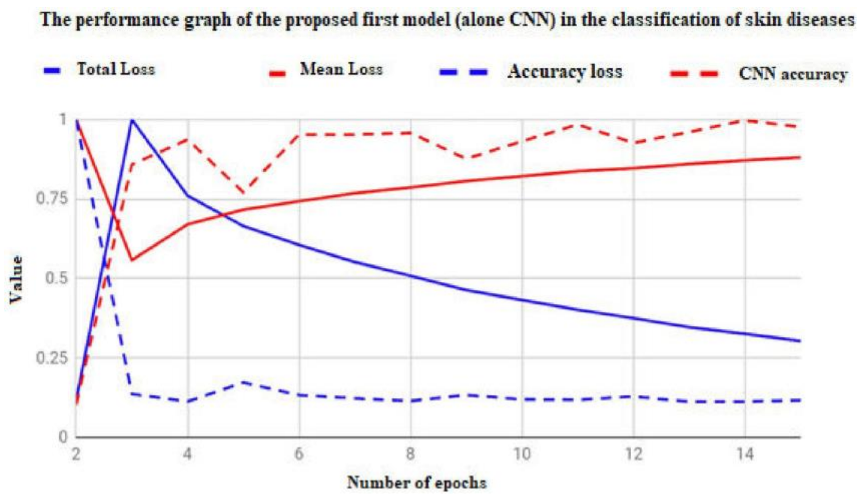

Table 5.3: Performance Graph using CNN method

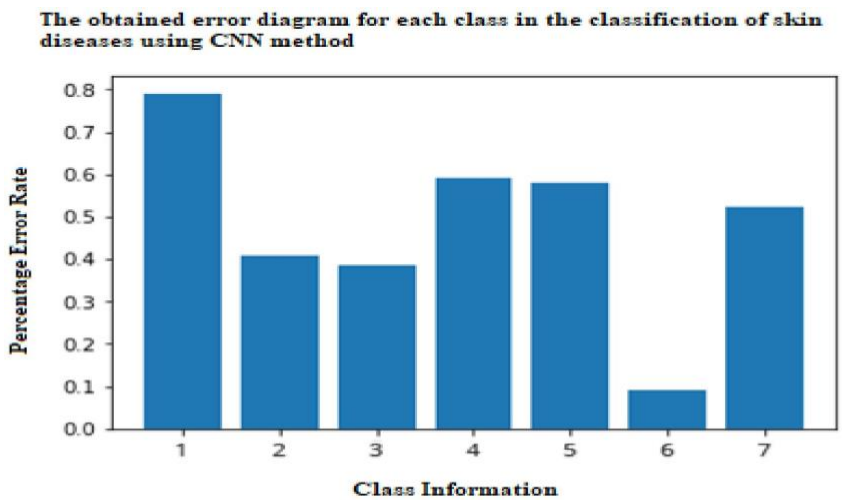

Table 5.4: Error diagram using CNN method

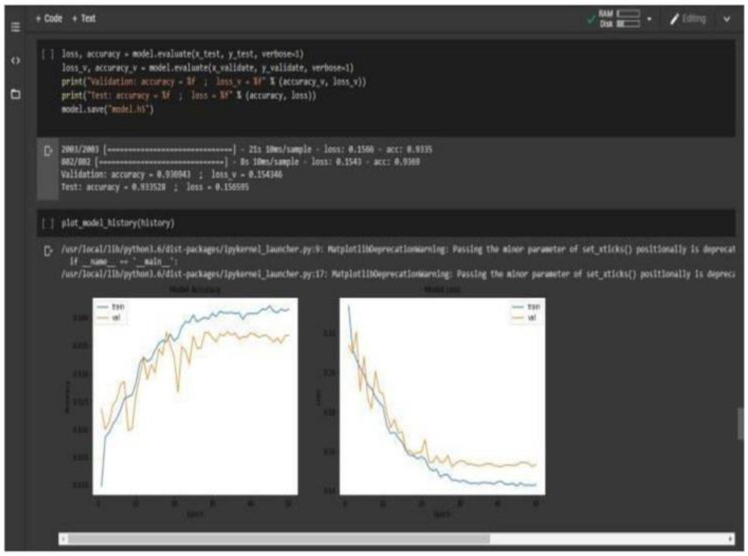

Table 5.5: Graphical Plotting

Chapter 6

CONCLUSION

In this work, deep learning algorithms are used to detect various skin diseases. Skin Disease detection is important to reduce death rate. Dermatological process to detect skin disease type is very costly compare to deep learning. No need of manual feature extraction from input image, since, deep learning networks extracts features automatically. Also, no need of image processing techniques. Here, ResNet50 is used, which is a transfer learning algorithm. To improve the performance of the system, data augmentation is employed. The augmented training image is fed into the ResNet50 network for training. After training completed the network is capable of detecting 8 types of skin diseases from input skin images.

The potential benefits of deep learning solutions for skin disease are tremendous and there is an unparalleled advantage in reducing the repetitive work of dermatologists and pressure on medical resources. Accurate detection is a tedious task that inevitably increases the demand for a reli- able automated detection process that can be adopted routinely in the diagnostic process by expert and non-expert clinicians. Deep learning is a comprehensive subject that requires a wide range of knowledge in engineering, information, computer science, and medicine. With the continuous development of the above fields, deep learning is undergoing rapid development and has attracted the attention of numerous countries. This can be further improved with large database and better features.

6.1 Advantages

The main merits of proposed model are:

1) Establishment of standardized skin disease image datasets. A large amount of data is the basis of skin disease recognition and the premise of acceptable generalization ability of the network model. However, the number of images, disease types, image size, and shooting and processing methods of the published datasets are considerably different, which leads to the confusion of different studies and the loss of the ability to quantitatively describe different models, Moreover, it is difficult to collect images of certain rare diseases. As mentioned above, there are numerous kinds of skin diseases; however, only approximately 20 datasets are available, including less than 20 kinds of skin diseases.

2) Interpretability of skin disease recognition Te progress of deep learning in skin disease recognition depends on a highly nonlinear model and parameter adjustment technology. However, the majority of the neural networks are “black box” models, and their internal decision-making process is difficult to understand. This “end-to-end” decision-making mode leads to the weak explanatory power of deep learning. Te internal logic of deep learning is not clear, which makes the diagnosis results of the model less convincing. The interpretability research of skin disease classification could allow the owner of the system to clearly know the behavior and boundary of the system, and ensure the reliability and safety of the system.

3) Intelligent diagnosis and treatment of skin diseases Deep learning can be used to address the increasing number of patients with skin disease and relieve the pressure of limited dermatologists. With the popularity of mobile phones, mobile computers, and wearable devices, a skin disease recognition system based on deep learning can be expected to be available to intelligent devices to serve more people. Using a mobile device camera, users can upload their own photos of the affected area to the cloud recognition system and download the diagnosis results at any time.

6.2 Future Scope

This project has an immense scope in the field of medicine and health care and can be continued for other such insightful innovations. Future work will be concentrated on improving the architectures used and other deep learning models other than this. Still there is a scope for improvement for skin disease detection system. This can be further improved, by using larger training set for training. That may improve performance of the system.

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A Screenshots

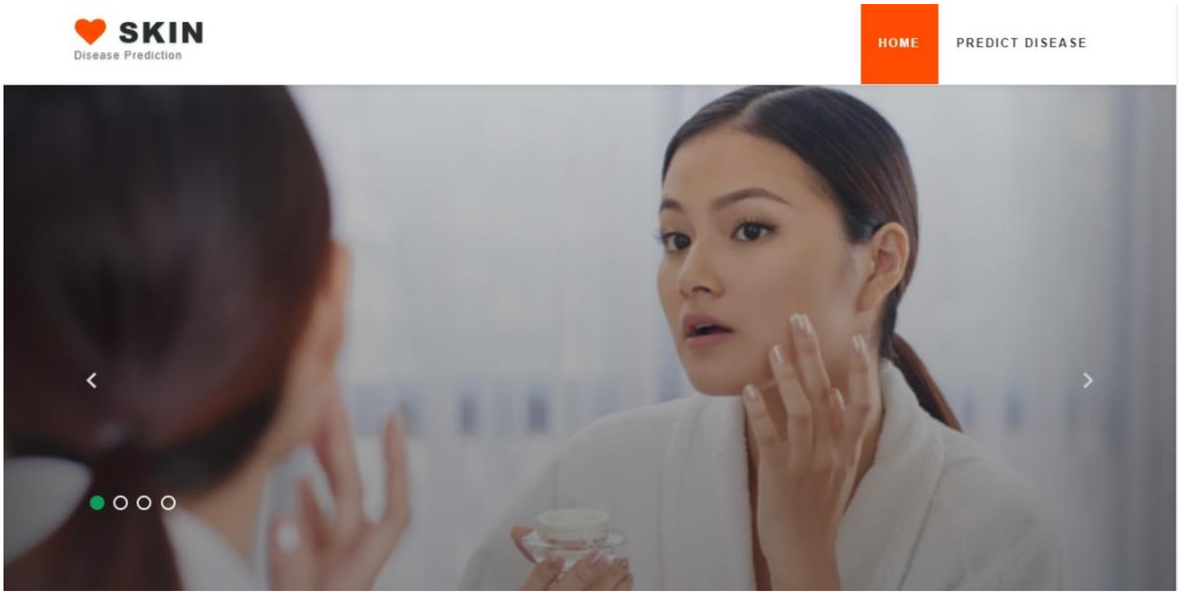

Figure A.1 : Home Page

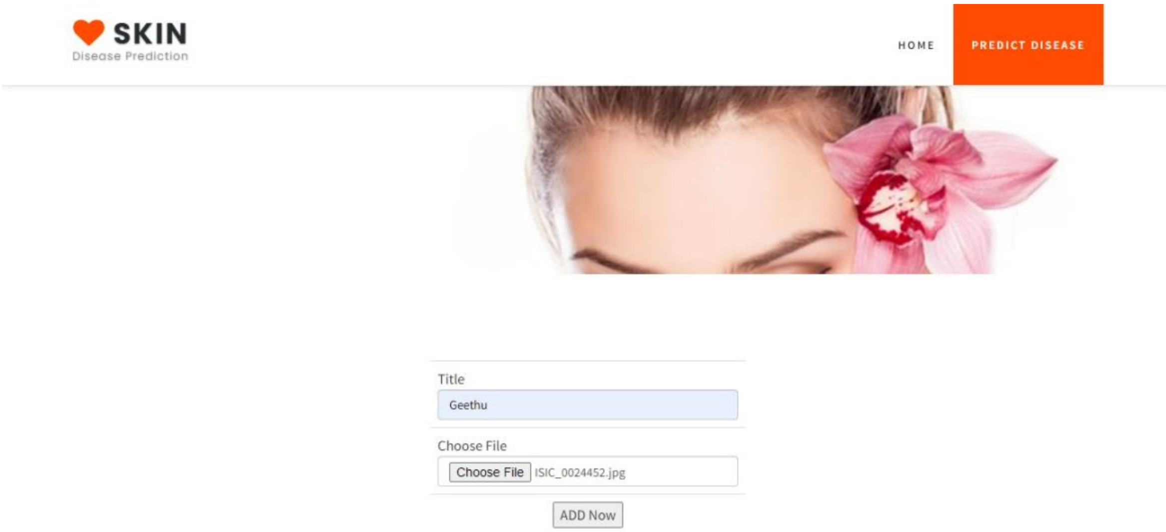

Figure A.2 : Browse Image Page

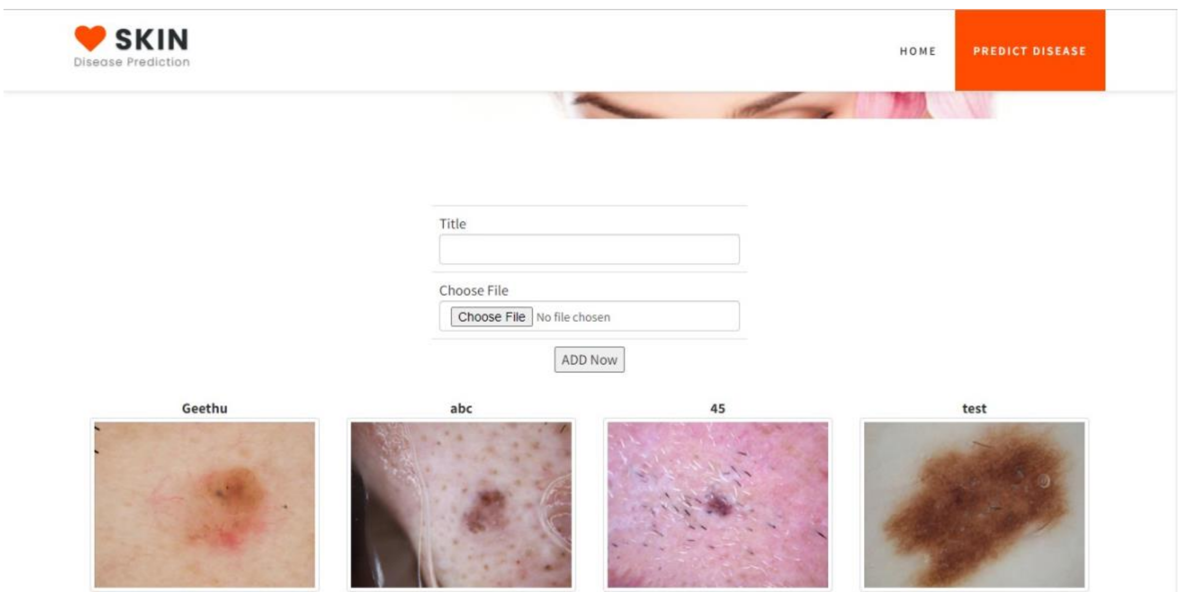

Figure A.3 : Uploaded Image Page

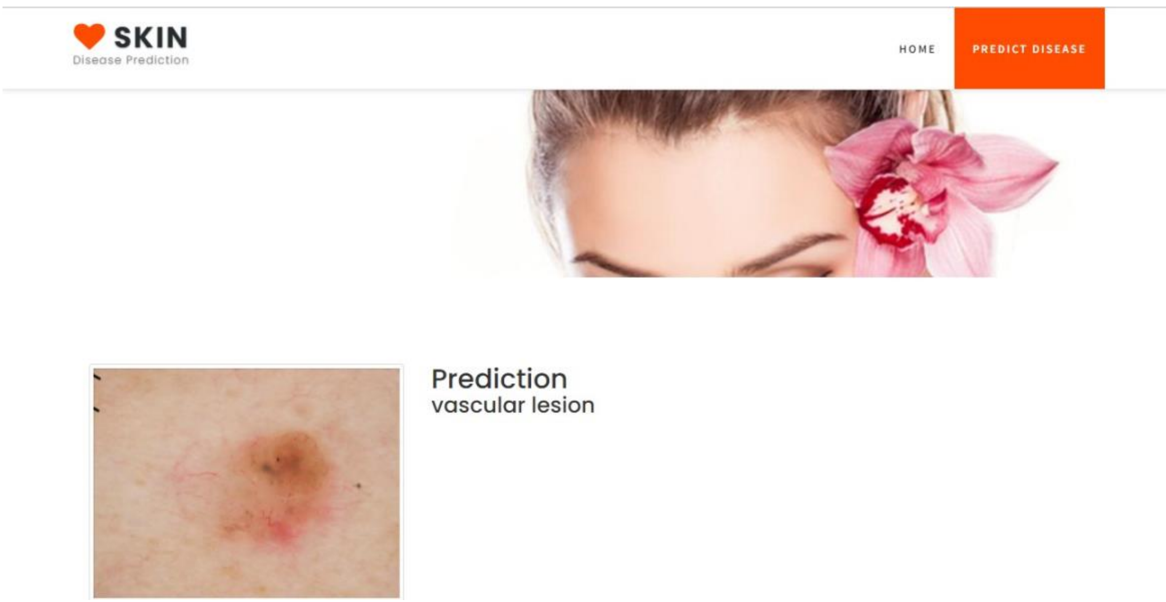

Figure A.4 : Prediction Page