International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Expert Automated System for Prediction of Multi-Type Dermatology Sicknesses Using Deep Neural Network Feature Extraction Approach

A. Kalaivani[1] and Dr. S. Karpagavalli[2] and [3]Dr. Kamal Gulati

Submitted: 03/11/2022 **Accepted:** 01/02/2023

Abstract: One of the most prevalent illnesses on the planet is skin issues. Due to the complexity of types of skin, and hair types, it is difficult to evaluate it despite its popularity. Consequently, skin conditions pose a serious public health danger. When they reach the invasive stage of evolution, they become harmful. Medical professionals are very concerned about dermatological disorders. The number of people who suffer from skin illnesses is growing substantially as a result of rising pollution and bad food. People frequently ignore the early indications of skin conditions. A hybrid approach can minimize human judgment, producing positive results quickly. A thorough examination suggests that frameworks for recognizing various skin disorders may be built using deep learning techniques. To find skin illnesses, it is necessary to distinguish between the skin and non-skin tissue. Through the use of feature extraction-based deep neural network approaches, a classification system for skin diseases was established in this study. The main goal of this system is to anticipate skin diseases accurately while also storing all relevant state data efficiently and effectively for precise forecasts. The significant issues have been addressed, and a unique, feature extraction-based deep learning model is introduced to assist medical professionals in properly detecting the type of skin condition. The pre-processing stage is when the input dataset is first supplied, helping to clear the image of any undesired elements. Then, for the training phase, the proposed Feature Extraction Based Deep Neural Network (FEB-DNN) is fed the features collected from each of the pre-processed frames. With the use of measured parameters, the classification system categorizes incoming treatment data as various skin conditions. Finding the ideal weight values to minimize training error is crucial while learning the proposed framework. In this study, an optimization strategy is used to optimize the weight in the structure. Based on the feature extraction approach, the suggested multi-type framework for diagnosing skin diseases has a 91.88% of accuracy rate for the HAM image dataset and identifies several skin disorder subtypes than the earlier models that can aid in treatment response and decision-making which also help doctors make an informed decision.

Keywords: *Classification, Deep neural network, Feature extraction, Skin condition*

1. Introduction

The biggest part of the body is the skin and is susceptible to damage from a variety of sources, including UV rays, tobacco, life choices, pigmentation, substance usage, infections, physical activity, and the workplace. The most common human illness is an infection that directly affects the skin. Skin diseases that are left untreated can lead to issues in the body, including the transmission of the illness from one person to another. So, by looking at the impacted area right away, skin diseases can be avoided [1]. The skin image characteristics are expanded to motivate work on developing a reliable and effective method for automatically identifying skin illness and its severity. Therefore, a substantial effort must be made to reduce mortality via the early diagnosis of skin diseases.

Assistant Professor, Department of Computer Science, Nallamuthu Gounder Mahalingam College, Pollachi, Tamilnadu, India
[2] Associate Professor and Head, Department of Computer Science, PSGR Krishnammal College for Women, Coimbatore, Tamilnadu, India
[3]Associate Professor, Amity University, Noida, Uttar Pradesh, India
[1]kalaivanimathsca@gmail.com / [2]karpagavalli@psgrkcw.ac.in /
[3]drkamalgulati@gmail.com / [3]Orcid ID: 0000-0002-1186-1426

Many scientists have used AI techniques to locate skin injuries at such an early age, which could be helpful for the quick recovery of skin conditions. About the research, a few frequently occurring skin conditions were chosen, including basal cell carcinoma, benign keratosis, actinic keratosis, and melanoma.

The most common type of skin cancer in humans, basal cell carcinomas are more common in older persons. Epidemiological updates show that BCC incidence is increasing year and that it is gradually increasing among young people. Although basal-cell carcinoma is unlikely to spread to distant areas or result in mortality, it does progress gradually and has the ability to harm nearby tissue. The delayed development of benign epidermal cells causes benign keratosis. On the neck, forehead, or chest, it usually appears black, brown, or pale. Beginning in early adulthood, benign keratosis is more likely to manifest. Other names for it include basal cell tumor.

The most deadly type of skin cancer is called melanoma. It also goes by the name malignant melanoma. It appears that the mole if it exists, has irregularly formed edges, uneven forms, and a variety of colors. A mole that has changed in appearance or changed in color over time. Malignant can be identified by changes in a mole's appearance, such as growth in size, skin disintegration, uneven borders or itching, and color change. Ultraviolet radiation in individuals with low amounts of pigment melanin is the main cause of melanoma.

Usually, actinic keratosis appears on the fingertips, eyebrows, and mouth—areas that are exposed to Ultraviolet rays. A telltale indication of this condition is a rough, bright red patch of tissue that grows into an expanded tumor and keeps growing. These illnesses have a serious impact on the particular patient, including their mental and emotional health. Therefore, one of the main areas of dermatological research is always the investigation of these diseases. It is important to note how drastically different the treatments are for these four skin conditions.

As a result, if treatment is directed, it could result in serious problems for people. Therefore, a patient only receives a cure if the right care is given to them in a timely way. Any skin condition that is identified using artificial intelligence techniques may be treated if it so chooses. By benefiting patients, these AI approaches can describe the seven skin-related disorders that were examined. Several systems enable accurate and competent illness identification. In the distinct field of medical imaging, the usage of machine vision and image processing techniques has increased significantly in recent years. Information diagnostics are required for speedy and accurate diagnosis due to the spread of several skin disease presentations, the scarcity and unequal distribution of experienced dermatologists, and the necessity for these factors.

Success is a result of advancements in medical technology based on lasers and photonics, skin infections may now be identified considerably more quickly and accurately. Such a diagnosis now has a high price and is scarce. In comparison to previous models, deep learning models categorize data and visuals more effectively. By automatically recognizing features in the input data, neural networks are able to adapt to changes in the problem under consideration and may overcome major difficulties. Using these most basic computer models, deep learning models will acquire the predicted data to discover and study the characteristics in the unexposed data patterns, producing noticeably high efficiency. However, without regard to how severe the skin condition is, it frequently results in death. Additionally, several doctors developed automated methods for identifying skin conditions, but these were ineffective. Since the methods now in use cannot reliably detect or predict the kind of skin illness.

As a result, it is quite difficult for the present approaches to appropriately diagnose the type of skin condition. Additionally, researchers concentrate on identifying the specific kind of skin illness. However, it is crucial to advance automated procedures to improve the precision of skin disease diagnosis. These problems are addressed by the introduction of deep learning algorithms that actively acquire data patterns and extract the features from the input utilizing the feature selection method. These methods can deliver precise diagnostic results while resolving common feature extraction problems. This has led researchers to think of employing a deep neural network to categorize the various dermatological conditions based up-on the frame of the affected region.

The following is about how the manuscript is set up: Section II discusses evaluations of publications on the detection of skin diseases. The problem definition, the motivation for the research, the description of the dataset, and the specifics of the suggested technique are all provided in Section III. Section IV provides more detail on the experimental findings. The final portion offers a conclusion and potential future directions.

2. Literature Survey

This section offers an overview of the number of studies on skin disease identification using image processing techniques and classification techniques. Some of the more recent works, among many others, are depicted as follows:

Nawal Soliman, & ALKolifi AlEnezi at el. in [2] proposed earlier time detection techniques for image analysis based on the deep neural network to pattern capture and use color to describe the attributes. S. Ra et al. [18] proposed the segmentation and classification method for identifying skin lesion regions in 2015 [3]. To do this, hair sections are separated after skin samples have undergone a filtering process to reduce unnecessary noise. For segmentation, the region growth method was applied, which repeatedly produced germ sites for scraping the infection region of the skin. As a result, the excised lesion site may be recognized by its color and texture. Then, to categorize illnesses, Machine Learning Model and k-nearest neighbor classifiers were combined.

Z. Wu et al. have proposed a neural network method for diagnosing skin conditions affecting the forehead [4]. China's skin image collection, a bigger clinical epidermis dataset with 2656 face photos, was obtained for analysis from Xiangya-Derm for this reason. For analysis, these input samples rely on three significant skin conditions—BCC, SCC, and SK—as well as additional prevalent conditions including Keratosis plasma, erythema, and autoimmune disorders. Five widely used network methods were created by the authors to categorize these illnesses in a dataset.

N. Zhang et al. [5] improved the whale optimization method and employed a classification technique (CNN) for the diagnosis of this disease. As a result, the performance metric is improved by combining the provided classifier with the optimization technique. But while retaining its computing speed, it still lags. Additionally, although the general performance has yet to be improved, which is regarded as the main issue, the examined classifier's performance has been acceptable in a few disorders.

M.Q. Kahan et al. [6] created a prediction system to distinguish malignancy from noncancerous in the same year using image processing techniques. The noise included in the input skin lesion pictures was first removed using a Gaussian filter. The impacted region was then identified by a segmentation approach. Improved K-mean clustering was created to address this. The extraction of the texture and color-based regions from the input image was then done using a unique hybrid super feature vector.

Electronic bio-impedance was employed by the authors Kotian, A.L et al. [7] to evaluate ulcers and skin malignancies. The difference between harmless vermin and skin cancer was determined using a multi-frequency sensitivity spectrum. For the purpose of segmenting macroscopic lesion regions, researchers Sundaramurthy, S. et al., [8] created a new recurrent probabilistic area approach. This approach essentially combines stochastic zones at the pixel level, followed by the national and regional levels, till resolution. The use of various algorithms for the classification and prediction of test datasets and records and data that are beneficial in promising applications can also be demonstrated using this method, which also elaborates on using a combination of machine learning along with optimization algorithms for the prediction and classification of various datasets with high accuracy.

The intention of Kotian, A.L et al., [7] was to increase the precision of skin disease classification by the integration of many forecasting models utilizing ensemble approaches. Unexpected disparities between the samples and populations under consideration cause ensemble techniques to underperform and are a problem when datasets are unbalanced. A framework of deep learning models has performed amazingly well in classifying skin conditions. The paradigm, however, has been shown to be incorrect for visuals with many lesions by real study. Designs for artificial neural networks demand more computational work and require a lot of experience to become accurate. Internal optical consistency is utilized in these architectures' cross-correlation-based feature categorization process, which assesses both temporal and spectral aspects when choosing features. Systems that use cross-correlation are noise-resistant. The projections are thus more accurate. Additionally, conducting work in the spectral domain necessitates a large investment in planning the study and gathering the data.

A model using computer vision and machine learning is suggested in [9] by Kumar, V., Kumar S., and Saboo, et al. The image's characteristics are retrieved, and algorithms are then used to identify six different illnesses with a 95% accuracy rate.

It was found from a review of the literature that Aziz, et al expert application of epidermis disease diagnosis using strategies like Naive Bayes, SVM classifiers, and Classifier methods was extremely necessary in [10] to help all people who want to learn about skin diseases that are being encountered which need details about skin diseases.

In response to problems such as poor contrast between the skin cancer region, fuzzy lesion border, typical tissue background, and a range of cancer area sizes, G. Zhang et al. [11] developed the edge detection of medical image samples on skin lesions in a manner similar to this. In order to separate the outcomes of melanoma, they focused on employing DSM-Network (deep supervised multi-scale network). Additionally supporting the contours improvement post-processing procedure is a conditional random field technique.

Skin sample images are processed using feature extraction techniques in [12], kin disease segmentation and identification using a dynamic-graph-cut technique, and classification using a KNN Classifier have been proposed by Balaji et al. It uses the Decision Tree algorithm as little more than a classification method.

3. Proposed Methodology

In this section, the suggested prediction model will reveal seven severe subtypes of skin disorders. Fig. 1 shows the suggested model for identifying skin diseases.

3.1 Research Gap and Design Characteristics

Skin diseases are being predicted quickly and with such batch processing using an autonomous skin disease detection system. Early detection of skin issues can help prevent skin conditions including skin cancer. The performance parameters for a combined technique of skin condition detection are covered in this section. In reality, there are variations in dimension, structure, width, brightness, and sharpness of source pictures, along with many other things.

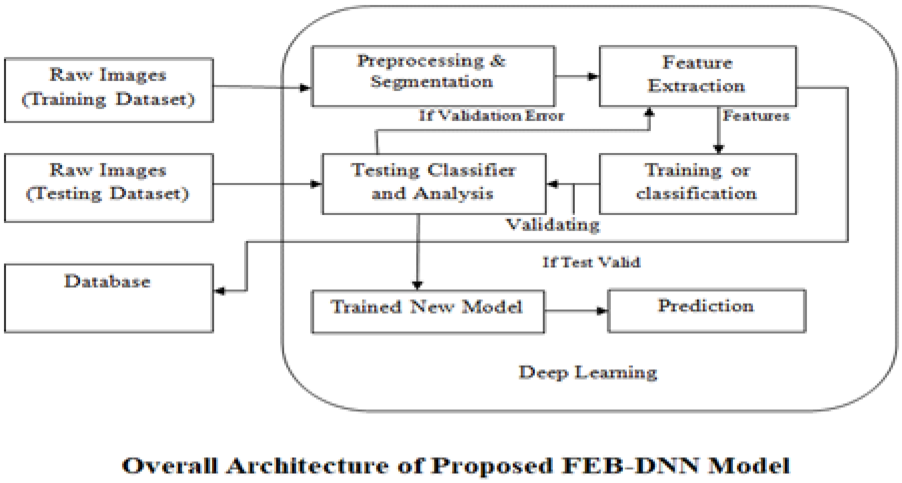

Fig. 1. The System Design of Skin Illnesses Classification using FEB - DNN Model

Additionally, accurate imagery separation is necessary for predicting skin diseases. The sickness classifier may become less accurate after cropping image segments to extract information. To create an efficient hybrid digital skin condition detecting method, some specified requirements must be met. The four fundamental needs include several other qualities like robustness, data segmentation, retrieval of data, and forecasting.

The capacity to recognize the injured skin image after it has been transformed by a variety of common image processing techniques, such as scaling, reformatting, translating, wavelet transformation, rotations, color mappings, distortions, and compressed, is one of these fundamental requirements. An additional prerequisite for a composite dermatological detection approach is metadata classification, which further splits the impact images domain for skin infection assessment. A segment splits an image into a large number of pieces or a limited number of regions (preliminary categorization).

The data extract intends to demonstrate the traits generated by the divided images portion. Effective classification of skin conditions is achieved by using these deduced features. Another crucial prerequisite for an automated technique of identifying skin disorders is standardization [13]. Using deep learning algorithms, skin disease prediction is possible. Skin conditions such as common, minor, uncertain, and melanoma are predicted.

3.2 Dataset Description

ISIC database samples of various classes are used for the study. The International Skin Imaging Collaboration (ISIC) is a developing standard for reporting on the methods, approaches, and lingo used in skin imaging. Similar to this, the skin Imaging Collaboration system (ISIC) has developed and is continuing to expand as an adaptable, freely accessible database of pathology prints of the skin to review and support the proposed automated diagnostic tools. Seven illnesses were selected for investigation from that dataset, totaling 10015 photos that were split into training (80%) and testing (the remaining 20%) phases using the suggested technique. The biggest publicly available skin dataset assembled from the ISIC collection, the HAM dataset, is where skin photos are taken. The location for this dataset at https://isic-archive.com/. The samples were collected from Australia and Austria over the course of 20 years. There are just dermoscopic samples in it, and pathology has confirmed 505 lesions.

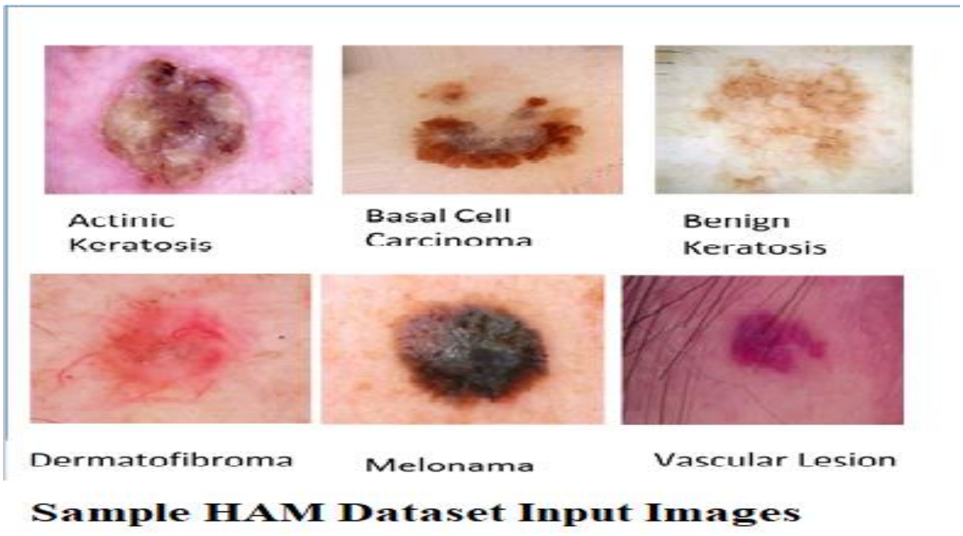

Fig. 2. Sample HAM Dataset Input Images

3.3 System Model

Researchers analyze and identify each image in a set of photos they received from a customer before evaluating them in our recommended system [13]. Then, a pattern extractor is used to extract information from each print that may be used to create a classifier. Thanks to the implemented classification method, the application could determine the illness for one current digital image of a skin infection acquired using a prescribed framework. Ultimately, our technique suggests medication therapies or guidance based on the expected course of a skin condition.

In this part, we go into further detail about the proposed techniques. A crucial step in the detecting process is picture pre-processing, which enhances the original image's qualities while removing noise like hair, cloth, and other art facts. In order to prepare the image for further processing, the main objective of a few parts is to enhance the value of the skin outer layer representation by removing unnecessary and excessive elements from the backdrop image. The effectiveness of the service may be considerably increased by a well-chosen collection of pre-processing methods.

3.3 Motivation of Proposed Work for Skin Images Categorization

Skin conditions can start inside an organ and spread to the skin, or they might start and present on the skin. These problems will be examined in this section [14]. Also mentioned in the design of a deep learning model for diagnosing skin conditions. By gathering patient data and symptoms, a specialist can diagnose skin problems. Then, a variety of logical indications are added to this list of known skin conditions and complaints.

The symptoms are also evaluated with information that the expert system has previously stored. If a diagnosis is made, the doctor proposes the condition as a probable root of the skin condition. To discover the cause of the skin condition, the doctor may occasionally refer the patient for further lab work. The test may be carried out to determine whether the sickness under investigation is brought on by a bacteria, parasites, viruses, or fungi [15]. A specialist must use multiple iterations to make a diagnosis when he is inexperienced or has never encountered the condition before. This is done by merging all possible outcomes, evaluating them against existing ones, and then narrowing the options. If the skin issue is successfully identified and treated during this phase, learning is said to have taken place. As a result, the expert depends on their knowledge and evaluation of the client in the event.

This section serves as an example of the sickness evaluation process, which entails the systematic collection and cataloging of skin illnesses for use in the deep neural network of the system. The vision is to develop automated information systems that can take data as input and use it to produce a proper diagnosis.

For accomplishing the multi-type skin disease prediction, the suggested architecture involves three steps. Pre-processing is carried out in the earliest stages to produce the qualifying picture. Noise reduction, contrast improvement, and hair removal are done in this step after the input database photos are gathered and supplied into it. The resultant pre-processed impression is used to extract color- and texture-based characteristics in the second phase, feature extraction. Based on statistical parameters like mean, sample variance, and deviation, color attributes are derived. These attributes go through a categorization stage before being processed further. The classification of several types of skin illnesses is a distinctive feature that is utilized to train and evaluates the model in the final stage. This phase is the foundation of the suggested system extracted deep neural networks with probability.

3.3.1 Pre-processing

The algorithm produces an improper result when there is noisy material in the image. For this reason, it is necessary to get high-quality images free of any noise in order to achieve the desired result. De-noising the input skin pictures is therefore crucial. The optimal de-noising technique will eliminate noise from the image without harming the edges. There are various methods for de-noising a picture. The best method for de-noising the image is to use a median filter, which replaces each pixel's value with the median of all the pixels in the region. By placing every pixel from the immediate neighborhood in arithmetical order, the median filter is evaluated. The middle value of the pixels in that position is instantly substituted for the pixel value in that location. The median filtering method for the sample input is mathematically expressed in the following equation.

Histogram equalization especially enhances the brightness of the image while also reducing noise. To get a high degree of contrast in the image, the effectiveness including a whole combination of features must be distributed. When a visual is closer to contrast, this strategy is helpful.

The research highlighted the ability of mathematical morphology as a method for dermoscopic picture hair removal. Hairs are considered to be image artifacts. The most difficult step in performing morphological operations is choosing the right structural element (SE), which must be done in accordance with the contour of the input sample. A compact segmented image with each input image having a value ranging from 0 to 1 or a low-resolution matrix makes up the portion of the image that is utilized as the feature map. The devised hair cleanup histopathologic processing subjects a contrast-enhanced input picture to structuring components and generates an output image of a similar size. Therefore, to reduce the effect of the disruptive artifacts, morphological processes including deformation and dissolution are used in this area. Here, the hair removal procedure is initially carried out using binarization.

The median filtering process of the input sample is mathematically expressed in the equation below.

$$F(i, j) = \text{Median}\{F(i + P, j + Q), (P, Q) \in k\} \quad (1)$$

F(i, j) shows the output of the mean average pixel value, where k is the rectangular pane parameters, (i, j)Ɛ (1, 2,...,r) ×(1, 2,....,k), r is the image height, and k is the image diameter. The input image smooth out the pictures and keeps the edges while performing the feature selection method, retaining just the key information.

3.3.2 Retrieval of Features from Attributes

To get a minimal, significant, and non-repetitive presentation of visuals, the feature extraction procedure is used. Since the feature extraction method used to extract features from samples directly affects how well a classifier methodology performs. This is accomplished by removing extraneous and unnecessary data from the skin imaging data. It has been demonstrated that a classifier with significant but tiny features would offer better accuracy metrics and need less memory.

In addition, the feature extraction stage speeds up the performance of recommended category computations. The pattern image processing technique will be completed at this point in order to differentiate between the many kinds of skin illnesses. These attributes are obtained by the identification of image features. The reason for choosing these characteristics is because the illness region is characterized mostly by qualities of texture and color.

Color statistics are used as a concise representation to extract the color characteristics. It has been demonstrated that the three low-order statistics can capture information about color distribution for the longest possible duration. It consists of the mean, standard deviation, and skewness, which are useful and effective representations of the color distribution of the input sample. Each pre-processed image has these three low-order statistical characteristics retrieved using the following mathematical formula:

The color statistics characteristics are defined as follows if the pixel intensity a^{th} value at pixels b^{th} is p_{ab}.

Mean - calculates the value of the mean $M_a = \frac{1}{N} \sum_{b=1}^{N} Pab$ (2)

The total amount of pixels in the output sample, in this case, N, is the result of preprocessing.

3.3.3 Multi-type skin disease prediction model based on FEB - CNN

The acquired data is then utilized to classify seven main skin illnesses using the proposed Image Feature Extraction Based Deep Neural Network Learning (FEB-DNN) structure. The basic distinction between Deep Neural Network (DNN) and a neural network (NN) is that DNN has a lot more convolution layer between the layers of nodes.

When there are a large number of accessible input samples during the training stage, deep learning-based approaches perform quite well. Therefore, a deep learning technique is used to define the suggested skin disease, prediction model. Similar to this, while training a typical DNN, each network neuron weight is updated each succession until the difference between contribution and production remains outside of acceptable limits. As a result, it takes time.

A unique Feature Extraction-based DNN was developed to improve conventional DNN is developed for classifying different skin diseases depending on the input features used. In this, the set of ideal weights for the interconnecting links are acquired using an optimization approach.

The suggested classification model for predicting the skin disease model's operational process may be divided into two parts. In the suggested model, the trained procedure takes place during the initial section, just like it does in traditional DNNs, while the assessment procedure occurs in the latter.

It is common to repeat the procedure until each desired predictor has been developed using eighty percent of the complete input data. As was previously said, the suggested model uses an optimization technique to speed up the training process and derives the output from the obtained probability values. Here, the best algorithm is utilized to efficiently create the probability values and give an ideal interconnection weights selection procedure between the connections interconnecting the DNN neurons to enable quicker classifier network training.

Believe of the input as $[I_a]$ where the output is defined by $1 \leq a \leq A$ and O. The input $[I_a]$ in this case is feature-extracted data from skin picture sets of arbitrary size (n). The $(n+1)^{th}$ output of the dermatological estimation method is O.

Consider that O is the outcome of the whole network and that OH in DNN, where there is frequently more convolution layer, is the result of multiplying each neuron's distinct input by the neuron weight of the first stated hidden neurons to get the output of the hidden layer. Similar to that, the weight components of the very first hidden neurons are multiplied by those of the second hidden layer, and so on while waiting for the arrangement is firm. Only two hidden layers are used in this instance to classify the layers.

In the first hidden layer, the aggregating equation with the bias of the neuron, which is technically expressed as follows, is applied to the balanced value provided by the input.

$$O_{H\_1}(i = 1, 2, \cdots, K) = \left(\sum_{a=1}^{A} Kia\ \ Ia\right) + b_i \quad (3)$$

Where b_i acts as bias with the use of a fixed value, and M and A represent the number of input and hiding layers in the top hidden layer. The input and hidden layers connectivity weight are known as K_{ia}.

4. Experimental Results

Verified implementation results of the described approach are shown in this section. The experimental findings in this part attest to the viability and efficacy of the suggested approach. The suggested technique is put into practice using Python 3.7.8 using the HAM10000 dataset as the working platform and the following is a full overview of its system: The application assists in demonstrating the excellence of the suggested research. Initial pre-processing of the input dataset is done in order to characterize seven major skin disorders. In this case, the brightness of the input sample is increased by removing the noisy information that was there. Additionally, morphological procedures are carried out. The following stage involves extracting color and texture information, which are then put into the proposed FEB-DNN classifier to categorize many types of skin disorders. Numerous performance indicators, together with Accuracy, Recall, Precision, and F1-measure, are computed to calculate the effectiveness of the suggested research. Additionally, the suggested algorithm is contrasted with current methods like the Classical CNN (Convolutional Neural Network) Model to support its efficiency.

The comparative results of state of art of Classical CNN model and implemented Novel proposed model on HAM 10000 dataset in expressions of correctness, re-call, F1-measure, and accuracy are given in Table 1.

Table 1. The different Model’s performance Indicators

Performance Indicators in Terms of Percentage	Classical CNN Model	FEB – DNN Model
Precision (%)	89.40	90.74
Recall (%)	89.68	91.12
F-measure (%)	89.56	91.64
Accuracy (%)	89.78	91.88

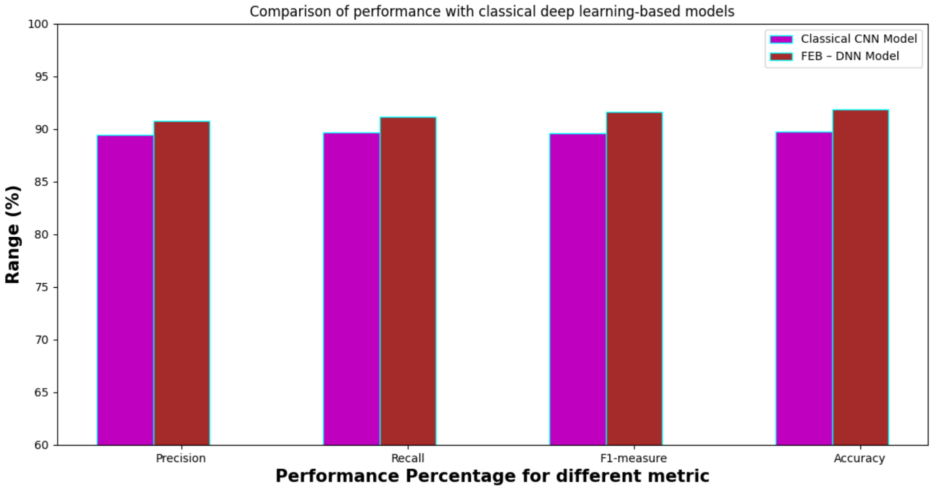

Fig. 3. Evaluation of Performance Indicators on HAM10000 Dataset

5. Conclusion

This study is meant to identify skin diseases using a software technique. The mentioned approaches are initially used to gather and pre-process the database samples. Then, for those pre-processed samples, attributes like color and texture are retrieved. A unique suggested FEB-CNN model is used to conduct the illness categorization using HAM10000 dataset and obtained results. To demonstrate the effectiveness of the suggested strategy, an investigation of the suggested system is evaluated with standing approaches. The suggested technique exhibits 91.88 percent accuracy in the detection of skin diseases, according to the overall analysis. To demonstrate the efficacy of the suggested technique, calculations of error rates are made. The resulted inaccuracy rate in place of the suggested methodology is 0.079, which is incredibly low compared to other current methodologies. Future studies will focus on end-to-end training of the proposed technique employing GPUs with high internal capacity in order to pursue end-to-end training using huge training datasets to minimize potential over-fitting in training.

References

[1] Hameed N, Shabut AM, Ghosh MK, Hossain MA (2020) Multi-class multi-level classification algorithm for skin lesions classification using machine learning techniques. Expert Syst Appl 141:112961

[2] Nawal Soliman ALKolifi ALEnezi “A method of skin disease detection using image processing and machine learning” at 16TH International learning & Technology conference 2019.

[3] Sumithra R, Suhil M, Guru DS (2015) Segmentation and classification of skin lesions for disease diagnosis. Proc Comput Sci 45:76–85.

[4] Wu Z, Zhao S, Peng Y, He X, Zhao X, Huang K, Wu X et al (2019) Studies on different CNN algorithms for face skin disease classification based on clinical images. IEEE Access 7:66505–66511 .

[5] Zhang N, Cai Y-X, Wang Y-Y, Tian Y-T, Wang X-L, Badami B (2020) Skin cancer diagnosis based on optimized convolutional neural network. Artif Intell Med 102:101756.

[6] Khan MQ, Hussain A, Rehman SU, Khan U, Maqsood M, Mehmood K, Khan MA (2019) Classification of melanoma and nevus in digital images for diagnosis of skin cancer. IEEE Access 7:90132–90144

[7] Kotian, A.L.; Deepa, K. Detection and classification of skin diseases by image analysis using Matlab. Int. J. Emerg. Res. Manag. Technol. 2017, 6, 779–784.

[8] Sundaramurthy, S.; Saravanabhavan, C.; Kshirsagar, P. Prediction and Classification of Rheumatoid Arthritis Using Ensemble Machine Learning Approaches. In Proceedings of the 2020 International Conference on Decision Aid Sciences and Application (DASA), Sakheer, Bahrain, 8–9 November 2020; pp. 17–21.

[9] S. Kumar and A. Singh, “Image processing for recognition of skin diseases,” International Journal of Computer Applications, vol. 149, no. 3, pp. 37–40, 2016.

[10] Aziz, A., Hartono, R., & Abdilah, R. (2020, June). Decision Support System for Detection of Skin Diseases in Smart Health development planning. In IOP Conference Series: Materials Science and Engineering (Vol. 858, No. 1, p. 012051). IOP Publishing.

[11] Zhang G, Shen X, Chen S, Liang L, Luo Y, Yu J, Jianwei L (2019) DSM: a deep supervised multiscale network learning for skin cancer segmentation. IEEE Access 7:140936–140945.

[12] Balaji, V. R., Suganthi, S. T., Rajadevi, R., Kumar, V. K., Balaji, B. S., & Pandiyan, S. (2020). Skin disease detection and segmentation using dynamic graph cut algorithm and classification through Naive Bayes Classifier. Measurement, 107922.

[13] Hameed, N.; Shabut, A.M.; Hossain, M.A. Multi-Class Skin Diseases Classification Using Deep Convolutional Neural Network and Support Vector Machine. In Proceedings of the 12th International Conference on Software, Knowledge, Information Management & Applications (SKIMA), Phnom Penh, Cambodia, 3–5 December 2018; Volume 1, pp. 14–20.

[14] Sandler, M.; Howard, A.; Zhu, M.; Zhmoginov, A.; Chen, L.-C. Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–23 June 2018; pp. 4510–4520.

[15] Maisano, R.; Tomaselli, V.; Capra, A.; Longo, F.; Puliafito, A. Reducing Complexity of 3D Indoor Object Detection. In Proceedings of the 2018 IEEE 4th International Forum on Research and Technology for Society and Industry (RTSI), Palermo, Italy, 10–13 September 2018; pp. 1–6.