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RESEARCH ARTICLE

A Comprehensive Joint Learning System to Detect Skin Cancer

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ABSTRACT Skin, the body's biggest organ and a barrier against heat, light, damage, and infection can be affected by many diseases. However, a correct diagnosis can lead to proper treatment. Skin diseases must be identified early to reduce skin lesion growth and spread. The medical field has a significant dependency on Information Technology and in this era, there is a need for a mechanism that can detect skin diseases at an early stage with higher accuracy capable of working with rapidly growing data. This research offers a joint learning system using Convolutional Neural Networks (CNN) and Local Binary Pattern (LBP) followed by its concatenation of all the extracted features through CNN and LBP architecture. The proposed system is trained and tested using the widely used publicly accessible dataset for skin cancer detection to solve multiclass skin disease issues. Furthermore, a comparison of results is developed between the architectures and their fusion. The demonstration of the results shows the robustness of the fusion architecture with an accuracy of 98.60% and a validation accuracy of 97.32%. Comparative results are also included in this research for better analysis.

INDEX TERMS Bioinformatics, CNN, computer vision, deep learning, image processing, LBP, skin diseases, skin cancer.

I. INTRODUCTION

Skin, the biggest organ of the human body can have a wide range of possible abnormalities. A study reveals the existence of about 3,000 skin diseases that can be harmful for this crucial organ [1]. Moreover, one-third of all malignancies diagnosed globally are skin cancers. Dermoscopy has improved the capacity to diagnose skin cancer in recent years. However, dermatologists face difficulties in making an accurate diagnosis of skin cancer since different forms of skin cancer may seem identical [2]. The late diagnosis is another a great hurdle for the dermatologists as we are relatively uninformed about the signs of many of these illnesses. Traditionally, skin cancer is detected via an examination, a physical examination, and a biopsy. Although biopsy is one of the most effective ways of diagnosing skin cancer, the procedure is time-consuming and unreliable.

The 4th Industrial revolution has significantly changed our daily lives in all aspects, and the medical field with no exception is revolutionized. So far, many medical systems have been developed to assist both patients and doctors in various ways, beginning with the registration process and ending with the use of technologies for disease diagnosis. Direct digital imaging for medical diagnostics has become a popular idea because of information processing power and machine learning algorithms. Different deep learning models have been developed and employed in medical diagnostics because of their ability to detect patterns in digital images [2]. Convolutional Neural Networks (CNNs) are the most effective method and have aided in the classification

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and identification of diseases in a variety of medical image processing applications [3]. Deep convolutional neural networks' (DCNNs') outstanding performance in image classification has led to its use in medical domains such as skin cancer classification [4].

In recent years, macroscopic and dermoscopic pictures have become the most preferred non-invasive tools for dermatologists to use in skin cancer detection [5]. Dermoscopy pictures are high-resolution skin images created by seeing deeper skin features to improve skin cancer diagnosis [6]. Dermoscopy's main disadvantage is the considerable training required. The scientific community has made great strides in creating computer-aided diagnostic techniques to address dermatologists' concerns [7]. As more and more data become available, computer-aided diagnosis improves. Retraining the system with fresh data is simple, and the basic model can be expanded to include a variety of additional medical data into its prediction pipeline [8].

This research offers a new model based on deep CNNs to identify seven types of skin cancer: Melanocytic Nevi, Melanoma, Benign Keratosis, Actinic Keratosis, Vascular Lesions, Dermatofibroma, and Basal Cell Carcinoma at an early stage. The proposed method is based on CNN, LBP and their fusion for feature extraction and is capable of working in complex environment i.e., in rapidly growing data and with ability to produce effective results with better efficiency.

II. RELATED WORK

Many researchers have proposed image-based processing approaches to identify skin diseases. Mahbod et al. [9] proposed a structure for the multi-class dermoscopic system of skin diseases. Predefined deep learning models AlexNet, VGG16, and ResNet18 are used in this paper to describe dermoscopic pictures of skin lesions. This system obtained the effects of classification of 90.63 percent through verifying the complicated pictures of the rivalry of ISIC 2017.

Tschandl et al. [10] proposed a framework designed for multi-class dermoscopy images skin disease scheme. This paper uses predefined deep neural networks AlexNet, VGG16, and ResNet18 to explain the dermoscopic images of skin lesions. By and through the system, the classification results were obtained by 90.63% by checking the complicated pictures of the ISIC 2017 competition.

Fujisawa et al. [11] proposed a predictive framework for the classification of skin diseases. For example, LeNet, AlexNet, ZFNet, VGGNet, GoogLeNet, ResNet, or SENet, the latest CNN model used in the clinical sector to incorporate skin sores extractors. During this study, 42 percent of dermatology graduates completed results during 14-class grouping, 60 percent board assured dermatologists, and 75 percent CNN classifier. The results of dermatology learners' parallel classification (malignant or benign) are 74%, board-assured dermatologists are 85%, and the CNN classifier is 92%. Nevertheless, there are no reference datasets used to measure the capabilities.

Hagerty et al. [12] proposed a fusion framework between deep learning and handcrafted features to get high accuracy for melanoma detection through dermoscopic images. It uses two types of dataset NIH SBIR 1636 images and ISIC 2018 challenge training dataset contains 10015 images. Handcrafted convolutional image analysis approach that detects pathological important melanoma feature extractor. The AUC of the integrated handcrafted features system (HC) with the ResNet50 model (DL) added to the data collection for ISIC 2018 is 83 percent and 94 percent without the HC features.

Zhang et al. [13] proposed a novel residual learning system for skin sore structure. The proposed system allows the use of leftover learning and a new perception learning paradigm to increase the skin sore ability sequence. The suggested neural network model based on ARL (Attention Residual Learning) convolution will adaptively underline the various pieces of skin injuries and thus achieve the best skin sore structure in class execution. Although prospective study includes studies into inappropriate learning and fine-grained classification of skin lesions.

Goyal et al. [14] proposed a framework for skin tumor recognition based on artificial intelligence (AI). Apart from the numerous inconveniences of AI approaches and systems, exceptional execution for skin malignancy detection. This paper helps to build effective estimations to help dermatologists assess skin conditions. AI enhances the accuracy of skin cancer discovery techniques. AI can express a standard for skin malignant growth recognition and be effective and extremely reactive along these lines.

Chen et al. [15] proposed a real-time skin disease recognition system. The artificial intelligence (AI) system is context-based development. It is a closed-loop information system among the user and remote medical databases. This system is to bring up-to-date datasets such as skin images, health conditions, and environmental information of the patient. The system uses three deep learning models such as LeNet-5, AlexNet, and VGG16, and is trained on the cloud for disease classification.

Pacheco and Krohling [16] suggested the computer-aided diagnosis (CAD) method detect skin lesions to overcome this issue. The dataset PAD-UFES-20 is a collection of biopsy-proven clinical images. These images were obtained through smartphones and clinical data. The system classified the un-labeled six different skin diseases frequently. The CAD system achieved 58.4% accuracy by classifying the biopsy-proven skin lesions while 100% accuracy for skin cancers.

Pacheco [17] describes the malignant development of the skin as one of the most known forms of illness. This has suggested different approaches in recent years to cope with the control of malignant growth position in the skin. The suggested dataset consists of 1,612 images of eight kinds of skin sores. The CNN's systems, GoogleNet, ResNet50/101, VGGNet13, and MobileNet are used for skin injury orders. Both equations take into consideration two kinds of datasets.

The results showed that all proposed models were given a specific overview of the clinical highlights. Both versions have a general standard precision of 76.4%.

Chaturvedi et al. [2] describe the utility of profound learning by using the MobileNet model for total skin malignancy classification. The Architecture was based on the HAM10000 dataset's 38,569 dermatoscopic images. The findings of the evaluation were compared, and the dermatologists were a leader. The position rate is 83.1 percent for 7 skin injuries.

Polat [18] suggested a CNN and one-versus-all categorization scheme for skin disorders (OVA). The use of CNN and OVA has discovered a variety of skin disorders on various levels. The benefit of OVA is that categorization is based on true and false for each class. As a result, the difficulty level decreased. As a result, when each class was assessed individually, the accuracy % in multiple classes improved. With 7 classifications, a single CNN achieved 77 percent classification accuracy in the diagnosis of skin illness. The combination of CNN and the one-versus-all approach achieved an accuracy of 92.90 percent. The suggested method, known as CNN-OVA fusion, may be used to a wide range of medical imaging classification issues.

Tschandl et al. [10] describe a unique system in telemedicine that system helps the detection of diseases. In this paper, an image-based AI system is proposed to control skin malignant growth. The outstanding quality of AI helps the clinical dynamic improve analytical precision over that of either AI or doctors and that the least experienced. This system used 34 layers of the residual network (ResNet34) trained on the publicly available pigmented skin lesion dataset containing seven skin diseases. The mean recall of CNN was 77.7% and the accuracy was 80.3%. This approach offers a framework for the future to improve human-computer collaboration.

Liu et al. [19] Proposed a structure for the exploration of melanoma. It uses a dataset of skin injury ISIC 2017. For the first time, skin sore division is done to get the ROI objects. The depiction of the academically mid-level aspect involves deep detail across picture tests, which is a delicate discriminating part. The system considers the difficult cases as being more concrete in this sense. Provisional results indicate that the proposed strategy beats better in the CNN techniques of the study.

Shanthi et al. [20] describe skin infections being the most prevalent health concern. In this paper, the suggested framework described the 4 skin diseases by using computer vision and AI. The CNN technologies used in this paper took advantage of elven layers. It uses pictures taken from the Dermnet repository. The directory contains several skin disorders, such as acne scars, seborrheic dermatitis, herpetic psoriasis, and urticaria. The problems looked at in this model include skin tone distinction, an illness condition, photo protecting framework necessities, and so on. The proposed results of the CNN classifier are 98.6% to 99.04%.

Chaturvedi et al. [2] present an automated computer-aided diagnostic method for multi-class skin (MCS)cancer categorization with very high accuracy in this paper. For MCS cancer classification, the suggested approach beat both professional dermatologists and current deep learning algorithms. We fine-tuned the HAM10000 dataset across seven classes and conducted comparison research to compare the performance of five pre-trained convolutional neural networks (CNNs) and four ensemble models. This article reports a maximum accuracy of 93.20 percent for the individual model within the collection of models and maximum accuracy of 92.83 percent for the ensemble model. Because of its streamlined design and potential to achieve better accuracy, we recommend using ResNeXt101 for MCS cancer classification.

Kritika Sujay Rao et al. [21] created a multiclass deep learning model to distinguish between healthy skin and skin that has a disease, as well as to classify skin diseases into their main classes such as melanocytic, melanoma, benign keratosis-like lesions, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. We trained our model using Deep Learning, which is a subset of Machine Learning that, unlike Machine Learning, makes use of huge datasets, reducing the number of classifiers significantly. The computer learns and divides the data given into degrees of prediction, producing accurate findings in a relatively short amount of time, thus encouraging, and helping Dermatology growth. Convolutional Neural Network (CNN) is one of the most used pictures categorization algorithms, therefore we utilized it.

The growth of CAD systems and related methods have been introduced since last 2 decades [6]. In [22], a skin disease detection approach was developed by F. Ercal. In the proposed method, the border of the skin lesion was obtained by doctors and the characteristics were constructed using the ABCDE rule. A business-related neural network classifier was approved to classify the skin lesions into benign or malignant. This system can achieve an 80% accuracy rate. In [23], another computer system named MoleSence was established by Opticom Data Research. This program also used the "ABCDE rule" to analyze the skin diseases images. In [24], a computerized melanoma detection system was developed by H. Gangster. In the system, computerized image segmentation was achieved by fusing the output of 3 algorithms and the segmentation accuracy is 96%. A 24-NN (Nearest Neighbor) classifier was used for skin cancer classification, and it achieved a 73% melanoma detection rate. The sensitivity and specificity are 87% and 92% for the "not benign" class in a two-class scenario. In [25], Handy scope was developed by the company called Foto finder in Germany. It merges a dermatoscopic with an iPhone and can extract lesion features. However, it does not incorporate lesion classification in the same device. Puneet Thapar et al. [26] worked on skin cancer detection using swarm intelligence algorithms as region of interest

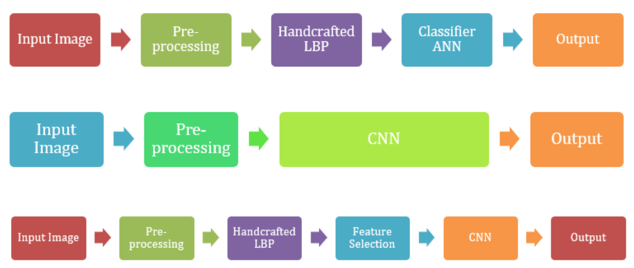

FIGURE 1. Architecture of Proposed Algorithm.

for skin lesion. The grasshopper optimization algorithm was used to get the best possible segmentation result. The authors used SURF (Speeded up Robust Features) for feature extraction. The skin lesion were classified in two classes using convolutional neural networks. The proposed algorithm gave an accuracy of 98.42% using the ISIC-2017, ISIC-2018 and PH-2 datasets. The authors [27] proposed a method to detect skin cancer capable of classifying the skin cancer in an automated way. They put a considerable effort on pre-processing of the dermoscopy images to produce the image in high quality. Several methods were used to remove the noise and parts which were not of any use. In a study, the authors [28] put an effort to determine the best possible feature selection and feature extraction technique to detect skin cancer. They drew a comparison of three the most common methods of the purpose i.e., SIFT (Scale-Invariant-Feature-Transformation) and HOG (Histogram-of Oriented-Gradients) and SURF (Speeded-Up-Robust-Features). It was found out that the performance of SURF was far better than the other both HOG and SIFT. However, on edge detection and texture analysis, HOG proved to be the best.

III. MATERIALS AND METHODS

The convolutional neural network has shown its significance in image processing and feature extraction, hence making it ideal for abnormality in organ diagnosis [29]. Furthermore, it can be operated on huge data, and the convolution portion of the proposed method, which is based on the detection of curves in pictures, makes feature extraction simple. This study revolves around the development of a model that will take an image as input and diagnose whether the skin has any illness and the kind of disease. Figure 1 shows the flow and working of the proposed algorithm.

A. DATASET

In this research, we used the HAM10000 (Human Against the Machine) dataset for training and validation of the proposed model [10], some glimpse of which is shown in Figure 2. The HAM10000 dataset is a gold 29 standard, with over 50% of skin lesions verified by pathology. Table 1 shows the breakdown the dataset and high degree of interclass resemblance, which makes categorization with the naked eye, a challenging task.

TABLE 1. Distribution of dataset.

Sr. No.	Name of Disease in HAM 10000 Dataset	Total Number of images
1	Actinic Keratosis (AKIEC)	327
2	Basal Cell Carcinoma (BCC)	541
3	Benign Keratosis (BKL)	1099
4	Dermatofibroma (DF)	115
5	Melanocytic Nevus (NV)	6705
6	Melanoma (MEL)	1113
7	Vascular Lesion (VASC)	142
	Total	10015

B. CLASS BALANCING

The classes in the final dataset are significantly unbalanced, which will add significant prejudice to the performance of the system. There are various methods to avoid this issue, such as data up-sampling, which increases the number of samples in smaller classes, and cost-sensitive learning [30]. We used the easier cost-sensitive learning in this system, which adds a new prejudice towards the small class by giving distinct weights to several classes based on their size. The Equation (1) shows this method.

$$class\_weight_i = \frac{\sum_{j=1}^{7} N_j}{N_i} \tag{1}$$

where Ni is the no. of samples in ith class.

C. IMAGE PREPROCESSING

1) IMAGE RESIZING

The input dermatoscopy images are normalized in various ways before feeding it to convolutional neural networks. These images are rescaled to a constant size of 28 × 28 before being fed into convolutional networks. The RGB photos are converted to grayscale images because the color information in the original pictures is not necessary to identify skin lesions. The red, green, and blue photos were converted to grayscale by summing the values of each pixel.

2) NOISE REMOVAL

Since most of the skin images are obscured by hair, it is difficult for networks to learn the characteristics [31]. Hence the skin images must be pre-processed to remove the blocking hair. With the assistance of Morphological filtering [32], we have attempted to eliminate hair noise from the sample images. Figure 3 shows the noise, such as hair, is presented in the images that partially covers the lesion. This makes it difficult for the neural network to retrieve important information from pictures, resulting in poor performance. The RGB images are first converted to grayscale for hair removal. Blackhat filtering is used to identify the black hair outlines in the grayscale pictures.

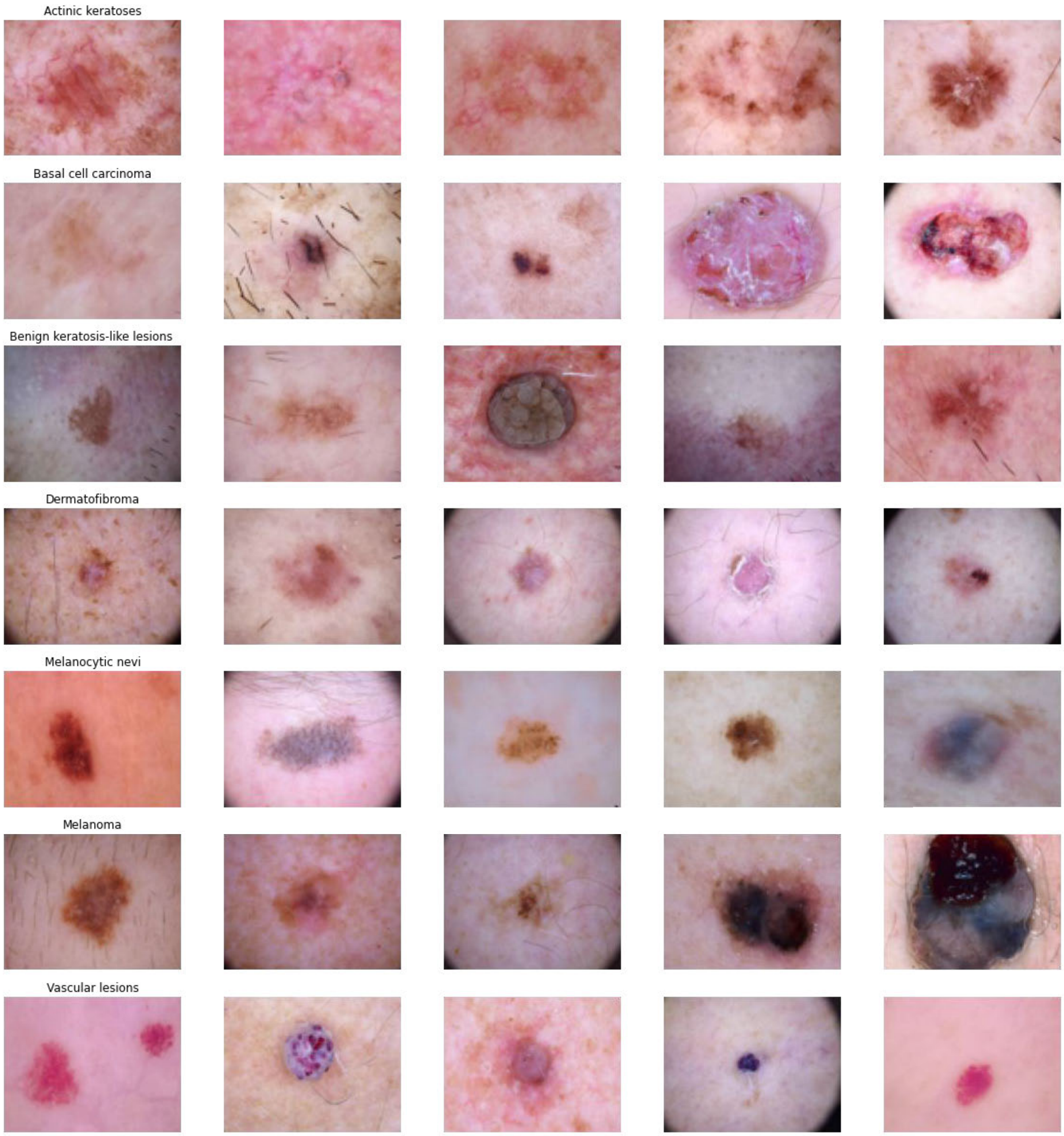

FIGURE 2. A Glimpse of Dataset.

The Blackhat image is the result of the morphological closure operation performed on the original image. The contours are used to construct the mask.

The mask only includes the hair area, and the non-zero pixels of mask are removed from the source picture using the image inpainting method. Although it eliminates some information from the images, this technique produces a very acceptable outcome for the removal of hairs. We have used the median filter to eliminate extra noise and artifacts. Finally, the most frequent kind of pre-processing method, picture scaling, is used. Using bicubic interpolation, we have scaled all the images in the dataset from 450×600 RGB to 28×28.

D. HANDCRAFTED METHODS

We have presented handcrafted traditional image analysis algorithms for detecting medically essential skin lesion features. The handcrafted method focuses on local feature detectors and descriptors, as well as holistic feature detectors and descriptors. These characteristics always determine the final recognition rates, through trial and error.

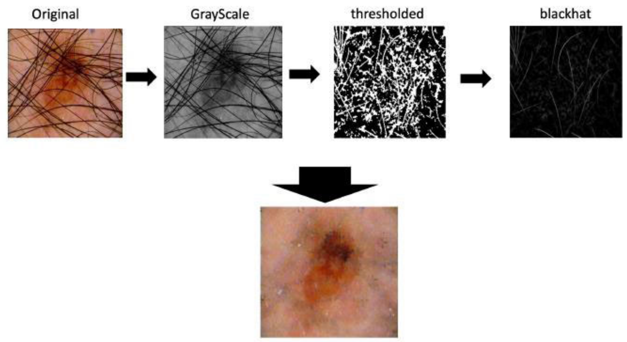

FIGURE 3. Noise Removal Algorithm.

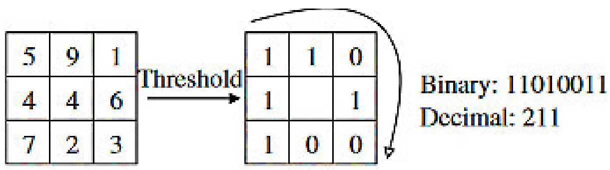

FIGURE 4. The Basic LBP Operator.

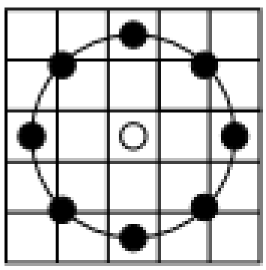

FIGURE 5. Circularly Symmetric Neighbor Sets.

1) LOCAL BINARY PATTERN

The very first LBP operator was presented by Ojala [33] which proved to be a strong texture description tool. The image's pixels are labelled by thresholding each pixel's 3 × 3-neighbourhood with the center value and treating the result as a binary integer. After that, the labels' histogram may be utilized as a texture description. A diagram of the basic LBP operator may be seen in Figure 4. Later, the operator is expanded to include different-sized neighborhoods [34]. Any radius and number of pixels in the neighborhood may be achieved by using circular neighborhoods and bilinearly interpolating the pixel values. We'll use the notation (P, R) for neighborhoods, which implies P sampling points on a circle with a radius of R. Figure 5 shows the example of the circular (8,2) neighborhood.

Uniform patterns [34] are another expansion to the basic operator. When the binary string is regarded circular, a Local Binary Pattern is called uniform if it has at most two bitwise transitions from 0 to 1 or vice versa. Uniform patterns include 00000000, 00011110, and 10000011. In their studies with texture pictures, Ojala et al. [31] discovered that uniform patterns account for just under 90% of all patterns when using the (8,1) neighborhood and about 70% when using the (16,2).

The LBP operator is denoted by the letters LBP u2 P, R. The subscript indicates that the operator is being used in the (P, R) neighborhood. Superscript u2 denotes the use of just uniform patterns and the use of a single label for the remaining patterns. The Equation (2) shows the labeled image of histogram is fi (x, y).

$$H_i = \sum_{x,y} I = \{f_i(x, y) = i\}, \quad i = 0, \ldots, n-1 \tag{2}$$

where n is the number of different labels generated by the LBP operator, and

$$I\{A\} = \begin{Bmatrix} 1, Aistrue \\ 0, Aisfalse \end{Bmatrix} \tag{3}$$

This histogram shows how the local micropatterns, such as edges, spots, and flat regions, are distributed over the whole picture. It's important to keep spatial information in mind while representing a face. The picture is split into regions R0, R1..., Rn for this purpose as:

$$H_{i,j} = \sum_{x,y} I\{f_i(x, y) = i\} I\left\{(x, y) \epsilon R_j\right\}, \quad i = 0, \ldots n-1, \quad j = 0, \ldots, m-1 \tag{4}$$

The labels for the histogram contain information about the patterns on a pixel-level, the labels are summed across a small region to create information on a regional level, and the regional histograms are concatenated to produce a global description of the face.

A common difficulty in face recognition from the perspective of pattern classification is having many classes and just a few, maybe only one, training sample(s) per class. As a result, more complicated classifiers are unnecessary, and a nearest-neighbor classifier is employed instead. Some possible variation sizes have been suggested for histograms.

Histogram intersection:

$$D(S, M) = \sum_i min(S_i, M_i) \tag{5}$$

Log-likelihood statistic:

$$L(S, M) = -\sum_i S_i log M_i \tag{6}$$

Chi square statistic:

$$X^2(S, M) = \sum_i \frac{(S_i - M_i)^2}{S_i + M_i} \tag{7}$$

By summing across I and j, we may extend all these metrics to the spatially improved histogram. When a picture is split into areas, some of the regions are likely to include more helpful information for differentiating between persons than others. To take advantage of this, each zone may be assigned a weight based on the significance of the data it contains.

E. CONVOLUTIONAL NEURAL NETWORK

A CNN architecture is developed to identify seven types of skin issues that depends upon

- The number of layers and their arrangement;

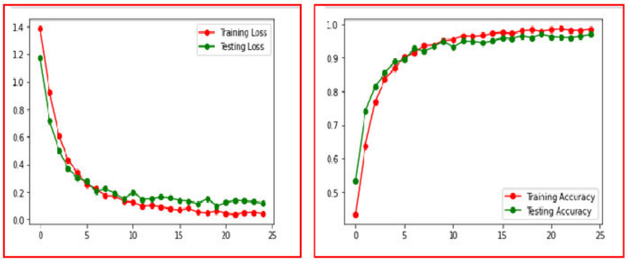

FIGURE 6. Accuracy and Loss of LBP Model.

- The number of training steps per epoch and the learning rate;
- Activation functions;
- Optimizer.

The network is employed by using four convolution layers and two max-pooling layers, a flattening layer, followed by three dense layers with Relu and SoftMax activation functions.

F. FUSION OF LBP AND CNN

The proposed algorithm is the fusion of both LBP and CNN for feature extraction of dermoscopy images which is an important step towards an early detection of skin cancer. The proven significance of convolutional neural networks in image processing and local texture information by LBP, combining both strengths will make able to enhance the classification of the skin cancer. Since the CNN focus on extracting the high level features and the LBP goes to capture the information from local texture, this fusion will be able to get the both characteristics and results in the generalized model. In the meanwhile, it will increase the robustness of the system as LBP will overcome the struggle of CNN dealing with the limited dataset.

The fusion is created by concatenating the features extracted by both techniques i.e., by LBP and CNN. After features extraction from deep learning and handcrafted, $\boldsymbol{X}$ denote as extracted feature from CNN is concatenated with Y as hand-crafted feature vectors, to form a better image depiction. Due to the lengthy size of a deep-learned feature vector $\boldsymbol{X}$ with small-sized hand-crafted feature vector Y has little effect on the accuracy, only deep learning-based feature vectors are fused with $\boldsymbol{X}$ independently to evaluate the classification accuracy.

As the concatenated feature vectors come from various sources, three extra thick layers with ReLU activation functions are created to further decrease the concatenated feature vectors to 1024 dimensions. This dimension reduction serves two functions. The first is that non-linearity in two ReLU layers allows the loss to be backpropagated and the weights to be changed, resultantly. The second goal is to shorten the processing time by using smaller dimensions. After training, feature vectors from several sources can be merged and used to characterize images. The learning rate is firstly set to 0.01, and then programmatically increased to 1/1.01 if the loss function does not improve. Finally, for classification prediction, a thick layer and a soft-max activation layer are added. Figure 12 shows the fusion architecture of the proposed model.

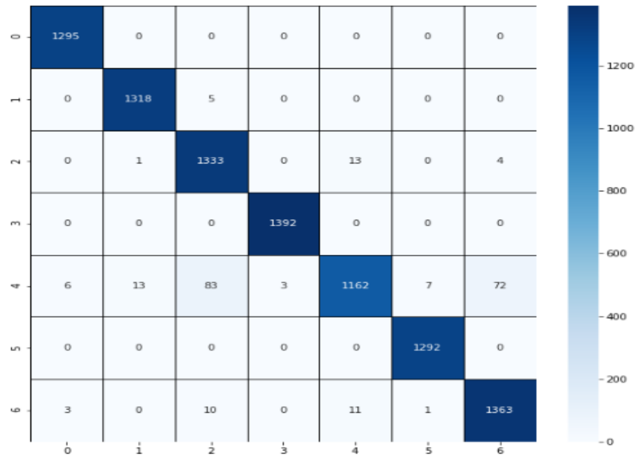

FIGURE 7. Confusion Matrix of LBP.

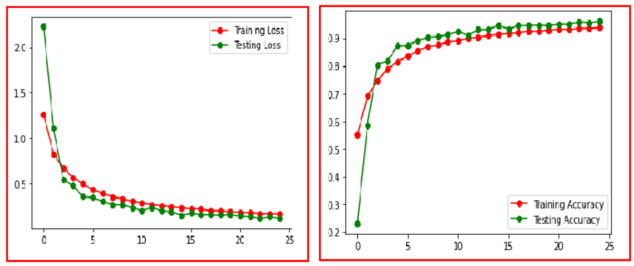

FIGURE 8. Training and Loss of CNN Model.

IV. RESULTS

A. RESULTS WITH LBP

The results with LBP are less satisfactory as compared to the fusion of CNN and LBP and CNN. The loss is calculated as 0.06% with the training loss of 0.14%. The results shown in Figure depicts the training accuracy of 96.31%, and the validation accuracy of 94%.

Figure 7 shows that the model detects the 1295 images of Actinic keratoses and intraepithelial carcinoma of class 0 accurately similarly 1292 images of class 5: pyogenic granulomas and hemorrhage and, 1392 images of class 3: dermatofibroma efficiently. While the model misclassified the classes such as class 2 of benign keratosis, class 1: basal cell carcinoma, and class 4 of melanoma. The model gives a poor classification for class 6 that consists of the melanocytic nevi images.

B. RESULTS WITH CNN

The results produced by CNN model are also satisfactory. Figure 8 shows the testing loss of 0.01% and the training loss as 0.12%. The same Figure depicts the training accuracy as 97.42%t, and the validation accuracy as 95.00% for this network.

Figure 9 shows that the model detects the 1292 images of pyogenic granulomas and hemorrhage from class 5, and

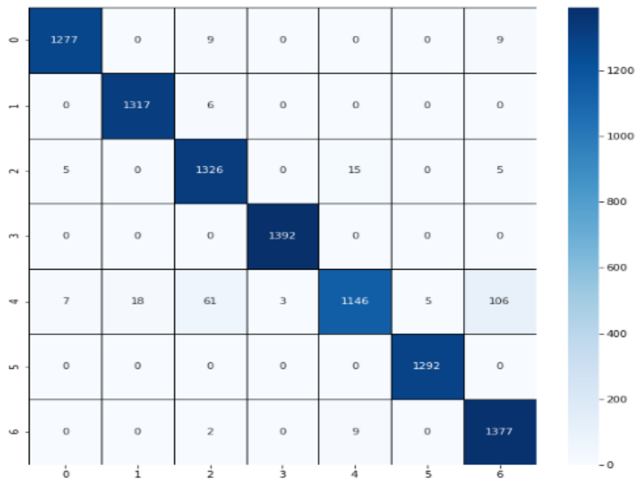

FIGURE 9. Confusion Matrix of CNN Model.

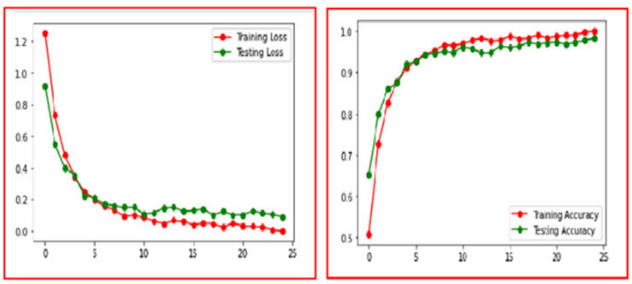

FIGURE 10. Training and Loss of CNN Model.

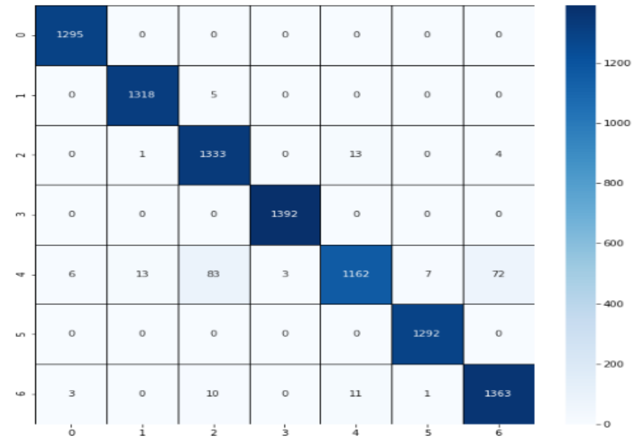

FIGURE 11. Confusion Matrix of LBP and CNN (Fusion) Model.

TABLE 2. Comparison of results.

Method	Accuracy (%)	Weighted Average (%)			Epoch	Training Time (s)
		Precision	Recall	F1-Score		
LBP	96	96	96	96	25	8.5
CNN	97	97	97	97	25	1.5
LBP + CNN	98.9	98	98	98	25	4.5

class 1 has 1317 basal cell carcinoma images efficiently. While the model misclassified the classes such as class 2 of benign keratosis, 1392 images of class 3: dermatofibroma, class 5: pyogenic granulomas and hemorrhage, and class 4 of melanoma. The model gives a poor classification for class 6 that consists of the melanocytic nevi images.

C. RESULTS WITH FUSION OF LBP AND CNN

The fusion model of CNN+LBP outperformed in terms of training and validation accuracy and loss. Figure 10 shows the training loss of 0.06% and the validation loss as 0.14%. The training accuracy outperformed with 98.37% and the validation accuracy with 97.32% for this network. Figure 11 depicts that Class 0 shows that the model detects the 1295 images of Actinic keratoses and intraepithelial carcinoma accurately similarly 1323 images of class 1: basal cell carcinoma and, 1392 images of class 3: dermatofibroma efficiently.

While the model misclassified the classes such as class 2 of benign keratosis, class 5: pyogenic, granulomas and hemorrhage, and class 6 of melanoma. The model gives a poor classification for class 4 that consists of the melanocytic nevi images.

V. DISCUSSION

The Proposed model is a fusion of the handcrafted Local binary method with the convolutional neural network. The suggested method is trained, verified, and tested using pictures from the HAM1000 File of skin lesions; classified into seven groups. To compensate for the imbalance between classes, all pictures are scaled to 28 × 28 using bi-linear interpolation, normalized, and data supplemented. Because of the significant class imbalance and the limited number of those presently accessible, multi-class skin lesion classification offers difficulty for training purposes; therefore, the hair removing technique is used to prevent misclassification. The following adjustment yielded the greatest results when using the suggested technique. To begin, deep model parameters are concatenated with LBP handcrafted feature. The loss function of all parameters is estimated through weighted Cross-entropy. Furthermore, the Adam optimizer starts with a learning rate of 0.0001 and subsequently reduces it by 20% after every 25 iterations if the validation loss function does not drop by 0.0001. Finally, early stopping terminates the learning process if the F1-score is not improved by 0.001 after 15 iterations to prevent overfitting before deep model convergence and to speed up the learning processes. The accuracy of proposed model is 98% which is very high perform all the state-of-the-art architecture. A deep highway CNN with feature fusion is given as a unique model. The training accuracy of the proposed system is 98.37 percent, and the validation accuracy is 97.32 percent.

Data preprocessing or skin hair removal will be a key factor to get the up to the mark results using the

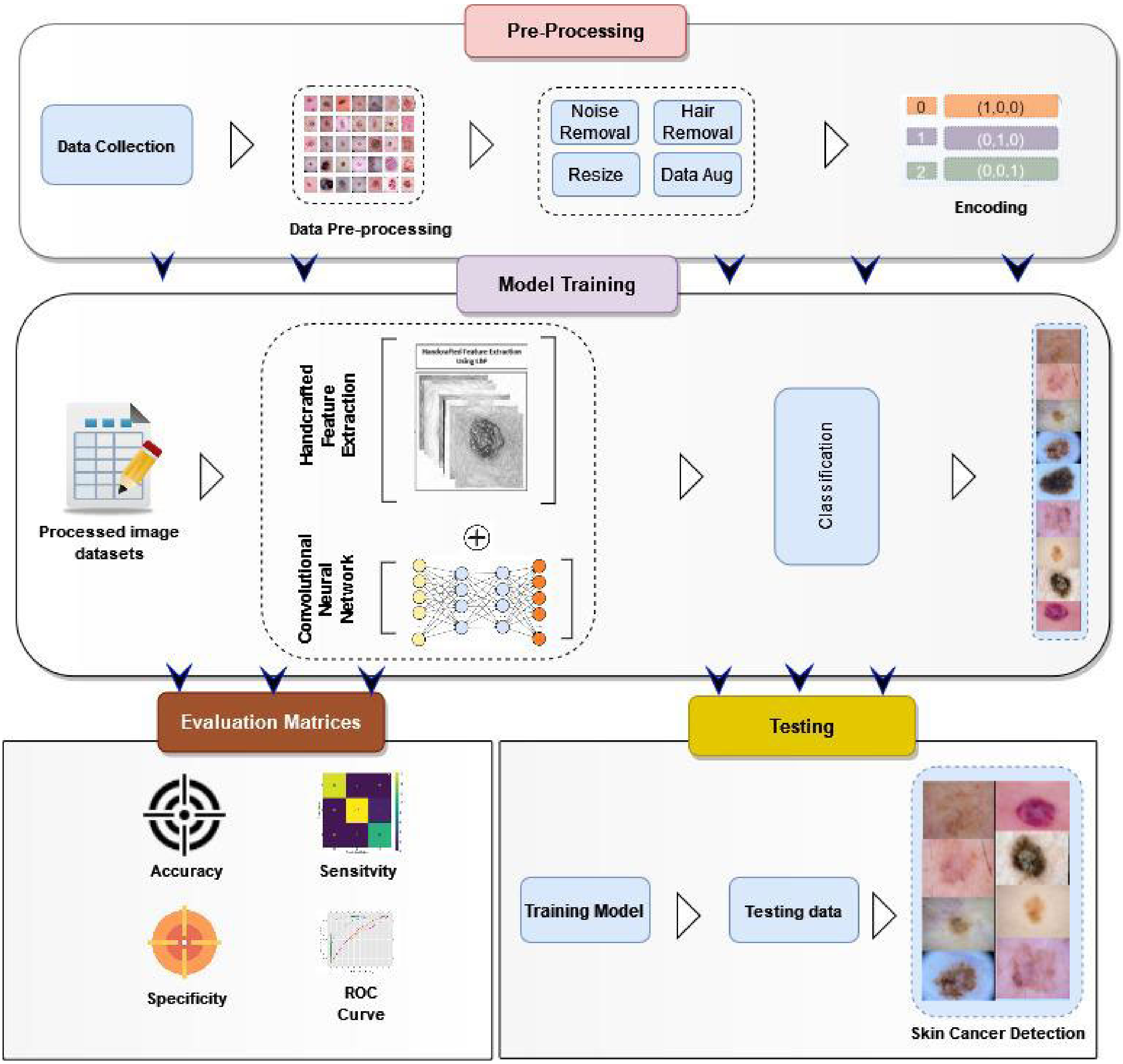

FIGURE 12. Fusion of LBP and CNN.

proposed methodology. A bad preprocessing can lead to the compromise in obtaining higher accuracy. So, it will be able to give outclass results only if the data is cleaned from the noise. Since we have used HAM10000 dataset for training of the model, it may not be able to detect other types of skin lesions. Moreover because of the different level of abstraction in the architecture of LBP and CNN models, the merging of the features may need some dimensionality reduction algorithm to get better results.

VI. CONCLUSION

The issue in early detection of skin cancer was a big issue, however the dermoscopy data available now a days has made it possible to detect skin cancer or any abnormality in the skin at an early stage. This study utilizes the HAM 10000 dataset for the detection of multiple skin disorders. The preprocessing is done before the feature extraction to remove any noise to get the nearest accurate results for detection. Since feature extraction is an important step to get the best fit, a fusion of handmade and deep learning features is used which gives an advantage over other conventional algorithms to detect the abnormalities in the skin as it includes the characteristics of both CNN and LBP i.e,, high level feature extraction and local texture information. Furthermore, it has sorted out the issue of generalization, the use of LBP will increase its practical applicability. In future, dataset may be extended, and skin lesions can be increased. Other fusion techniques may be explored with different handmade characteristics, as well as other classifiers. The proposed methodology will also be cross validated with extensive datasets.

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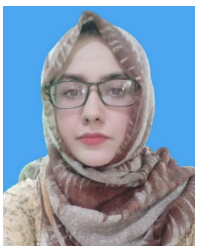

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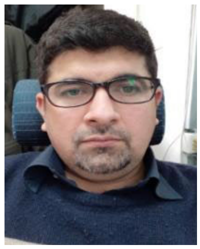

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