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Analyzing Skin Disease Using XCNN (eXtended Convolutional Neural Network)

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ABSTRACT

Skin disease is one of the major concerns for clinicians and researchers. Fungus, germs, allergies, and viruses are the main causes of skin diseases. There has always been unsaid competition between conventional and advanced computing-based techniques, and with these new techniques, cost of treatment is also being reduced drastically. In this paper, a deep learning-based model named eXtended Convolutional Neural Network (XCNN) has been proposed to classify three types of skin diseases (i.e., acne, rosacea, and melanoma). XCNN is easy-to-use, economic, and accurate. It will help clinicians to identify and categorize such diseases at the initial stage through automated screening. The proposed work is designed for multi-classification that takes digital images and applies XCNN to identify the type of disease. The model has been built on the dataset of the various skin disease images. It gives 95.67% accuracy in recognizing the diseases with improved recall, f1-score, and precision values compared to other state-of-the-art models.

KEYWORDS

Acne, Convolutional Neural Network (CNN), eXtended Convolutional Neural Network (XCNN), Melanoma, Rosacea, Skin Disease

INTRODUCTION

The skin is the body's most unique and biggest organ. It consists of blood vessels, lymphatic vessels, nerves, and muscles that enable it to perspire, detect external temperature, and protect the body. In addition to functioning as a sensory organ for the external environment, the skin protects the internal organs and tissues within the body against toxic substances, bacteria, pollutants, the sun's ultraviolet rays, and genetic skin diseases (Abunadi et al., 2021). In contrast, the skin may restrict the loss of

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lipids and water from the epidermis and dermis to sustain the skin's protective barrier. However, the clinician has difficulty distinguishing the kind of skin disease and its stage during the evaluation phase. The complexity of skin diseases is difficult to analyze at an early stage. Consequently, it is more difficult for medical practitioners to recommend potential medication and treatment to the patient.

Skin diseases include a wide variety of conditions that affect the skin, including genetic diseases (Acne, Rosacea), bacterial infections (Cellulitis, boils), viruses, fungal infections (Yeast, Ringworm), allergic reactions (Eczema, Hives, itching), skin cancers (Melanoma, Nevus, Basal, Squamous) and parasites (Scabies, Mites), etc., the symptoms may include a bump, rash, or a dry patch. Although, most skin disorders develop in the layers of the skin (Kshirsagar et al., 2022).

Skin is the first organ of the body to reveal detectable signs of underlying disease because of its appearance and accessibility. Skin abnormalities are typically indicative of severe diseases. In this respect, classifying skin disorders and symptoms can help clinicians predict skin disease stages. It can also assist in determining the level of severity. However, a few skin diseases are known to show symptoms after several weeks or months, leading to the spread of the disease at a severe level in the infected area. This may have several reasons like inadequate medical data for the said disease, confusion in classifying the type of disease at the initial stage, expensive medical diagnosis equipment, time consumed in a clinical tests, etc. However, the advancement in medical technologies has made the possibility of diagnosing diseases quickly and more accurately, but such diagnoses are still limited to some parts of the globe (Wu et al., 2019). It is also very costly and unaffordable for every person. In this context, "deep learning" based techniques may be useful in quick analyzing clinical information and concluding. It is one of the domains that may contribute significantly to the functional and accurate identification of several skin problems.

Among all skin diseases, Acne is the eighth most common disease in the world, affecting more than 681 million population (Flohr et al., 2021). Acne occurs when clogged skin follicles clump together and enlarge due to a blockage created by oil from glands, germs, and dead cells. Rosacea is also a common skin disease affecting more than 415 million people worldwide (Van Zuuren et al., 2019). Rosacea is a chronic skin condition that causes redness and pimples on the face. It can also thicken the skin and create eyesight problems. Melanoma is the nineteenth most commonly occurring type of skin cancer in the world, having 300,000 new cases in 2018 worldwide and 132,000 globally each year (Zhang et al., 2020, Nahata et al., 2020). In recent years, cancer has surpassed heart disease as the leading cause of mortality in humans. Approximately nine million people die each year, with 70% of these fatalities occurring in nations with low living standards (Curtin et al., 2020). This was owed to a delay in consulting medical experts at the start of the disease, an increase in the level of infection, and a lack of the necessary treatment, which turned into skin cancer and resulted in death. Often patients are unaware of the type of skin disease they are suffering from and how lethal it can be for them. Melanoma is a type of skin cancer that develops from melanocytes, the pigment-producing cells in the skin. This type of skin cancer is also known as Malignant Melanoma. It is the most severe type of skin cancer, with a mortality rate of approximately 20% if cancer doesn't get detected at the early stage. In most cases, it is possible that skin diseases may be converted into skin cancer, so it is vital to diagnose and proper medication for the disease at an early stage to stop susceptibility to infection (Linares et al., 2015).

Usually, diagnosing a skin disease takes more time and causes a financial burden on the patients. People in developing countries generally ignore primary symptoms and avoid the necessary treatment at the start of the disease. As a consequence of the above challenges, treatment becomes more complex. Using a deep-learning technique, namely eXtended Convolutional Neural Network (XCNN), these challenges mentioned above may be resolved by analysis of microscopic images of infected skin. Deep-Learning techniques enhance the image quality at the initial stage through segregating regions, pre-processing methods, and detecting lesion areas from healthy skin to emphasize the infected region. Subsequently, essential features are retrieved from each image and differentiated from other images with the same features. Eventually, the features are sent into the classification stage in order

to classify every region appropriately. The correct categorization of skin disorders would facilitate providing superior medical treatment to patients. At the initial stage, data is collected and applied to the proposed model, which identifies the features of the infected skin based on the training and classification of the skin diseases.

In the proposed work, a state-of-the-art comparison has been made with classical and recent deep learning-based models, i.e., CNN, AlexNet, Model (Single-instance optimized CNN), AcneNet, KNN, and MobileNet V2-LSTM, etc. Three other parameters such as precision, recall, and F1-score have also been taken for comparison, including accuracy. This work would genuinely help the medical practitioners diagnose skin diseases (i.e., Acne, Rosacea, and Melanoma) at the primary stage of the treatment with the minimum potential workforce. Thus, it will assist patients with economical and reliable treatment.

The remaining portions of the work are structured as follows: Section 1 discusses the purpose of the proposed work, an overview of the proposed work, the novelty of the proposed work compared to CNN, and a summary of the proposed methodology. Background information, a literature review, materials and techniques, and the suggested approach are covered in sections 2 to 4 of the paper. Later, experimental work and analysis of results, confusion matrix, evaluation technique, classification report, and comparative analysis are discussed. Section 6 covers the paper's conclusion and future work is discussed in section 7.

OBJECTIVES OF THE PROPOSED WORK

The proposed method has the following objectives.

1. To overcome the limitations of CNN.
2. To classify skin diseases with maximum accuracy.
3. To improve the acceptability of the model for the classification of various skin diseases in a faster and smoother manner.

OVERVIEW OF THE PROPOSED WORK

The parameters of the proposed method have been tuned in such a way that the model can attain the highest accuracy with minimum time. The basic Convolutional Neural Network (CNN) model has been tuned enough and modified by discarding layers that were not required and took unwanted time. Rectified Linear Unit (ReLU), Softmax activation functions, and additional layers have been used, which extracted more features accurately and efficiently without putting the model into an overfitting condition. The proposed method has been improved and optimized by using max-pooling and dropout layers for achieving an accuracy of 95.67%. A number of different layers have been evaluated several times while training data to capture the loss and accuracy of the proposed method. Convolutional layers, max-pooling layers, activation functions, dense layers, and dropout layers have been tuned to give the minimum loss in model training. Additionally, the layers and functions which are not required have been removed, which resulted in the final execution time of the method has been reduced without affecting the accuracy of the method. Considering all the improvements mentioned above in the proposed "eXtended Convolutional Neural Network" (XCNN) have been applied to solve the skin disease detection and classification problem with optimal accuracy. The accuracy in the classification of skin disease has been improved using this method.

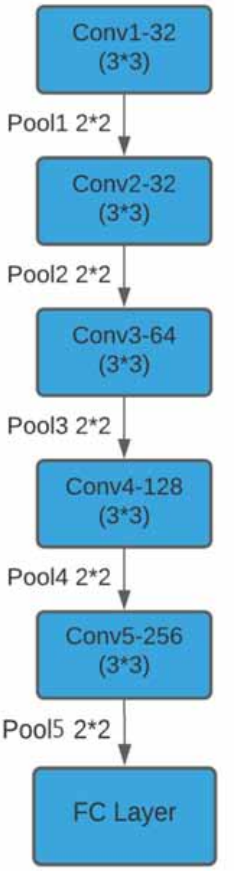
Figure 1 represents the sequentially stacked layers used in the XCNN. The main building blocks of XCNN are: Convolutional layer (Conv), Pooling layer (Pool), Rectified Linear Units layer (ReLU). The three layers have been connected to the multi-layer neural network called the fully connected layer. The fully connected layer (FC) signifies the dense, dropout and flattened layers.

Novelty In the Proposed Work Over CNN

XCNN is an optimized deep learning-based model that is a well-tuned version of CNN. Each layer of CNN has its own predefined set of parameters whereas the parameters passed in XCNN are optimally defined. XCNN has five conv2D layers, while in CNN, there is no upper limit defined for the same. Every conv2D layer in XCNN has been followed by a ReLU activation function and a max-pooling layer to maintain the dimension of the image. On the other hand, either a max-pooling layer or an average pooling layer is used in CNN.

In XCNN, four dense layers with a required set of parameter values have been passed in a specific order. There is no fixed standard on how many dense layers with different parameter values can be used in CNN. Dropout layers are used in XCNN to help in preventing the model from going into the overfitting region. In CNN the usage of the dropout layer is optional. In XCNN, only ReLU and softmax activation functions are used. Whereas in CNN, various activation functions like sigmoid, Softsign, Exponential Linear Unit (ELU), ReLU, leaky ReLU, etc., are used. Every layer of XCNN is optimized with appropriate parameter values. The order of the layers to be applied is predefined and fixed. The parameters of XCNN are tuned at their optimal levels to avoid going into over-fitting and under-fitting regions which helps the XCNN graph curve to fall in the category of the good curve.

Figure 1. Sequential stacked layers of the proposed model



XCNN has optimized numbers of layers; every layer is well-tuned, which provides higher accuracy and reduced computational cost compared to CNN.

Summary of the Proposed Methodology

The proposed methodology starts with receiving input images through the convolutional layers. Then the images are divided into different convolutional layers. Each layer processes a different feature of the image. After that, the ReLU activation function is applied which replaces all the negative values with zero and restricts the exponential growth in the required computation. Max-Pooling has been used to reduce the matrix size of the image. After that, the image (image's matrix) is again sent through the convolutional layers to conduct feature extraction from the image. Then ReLU activation function is applied to produce the resultant image. After completing the role of ReLU, max-pooling is applied to reduce the size of the image. The image is sent through the convolutional layer again for feature extraction then the dropout layer is applied after the ReLU activation function and max-pooling are completed. At this stage, some neurons from the existing layer are kept separate and not linked to the dropout layer. Overfitting has been reduced by using the dropout layer. The convolutional layer, ReLU function, dropout layer, and pooling layer have been executed three times. Flatten is applied next with dropout, and a dense layer is used, then the fully connected layer is formed. The image's matrix is converted to a vector form by the flattened layer. The ReLU activation function is applied to eliminate the negative value and convert them to zeros. The dense layer is used four times before using the ReLU activation function. The significance of the dense layer is to decide whether or not each neuron is connected to the existing layer. The dropout layer is used after the dense layer. Finally, the softmax function has been used to classify the image into groups, which has reduced the overfitting curve by minimizing the loss in training. Layer-wise operation of the proposed model is shown in Figure 2.

BACKGROUND DETAILS

Convolutional Neural Network

Convolutional Neural Network (CNN) which is also known as ConvNet, is an algorithm of the deep neural network which is mostly used to analyze visual imagery by extracting essential features from the input image (Singh AK. et al., 2021). Performance-wise, CNN is better than its counterpart traditional algorithms for image processing. It extracts the essential features from the image for better prediction in terms of recognition of the objects. It stores the weights associated with the extracted features to reuse further operations (Yamashita et al., 2018). The architecture of CNN conceptually mimics the human brain, where each neuron performs its assigned task through data processing and communicating with other neurons (Kim, Y., 2014). Figure 3 depicts a basic CNN architecture. Convolutional and pooling layers are applied to the image coming as input. The resultant matrix obtained is converted into the column matrix and then the extracted features of the image are received.

LITERATURE SURVEY

A literature survey of the neural network-based methods/models with related working details and findings is shown in Table 1.

Table 2 explores the limitations of the existing proposed models for the classification of similar diseases that motivated to overcome these limitations and provide a better solution to clinicians in their treatment.

After reviewing all the classical, similar, and new techniques, the proposed model has been implemented. The model is tuned with optimized network parameters to overcome low accuracy

Figure 2. Layer wise operations of the proposed model

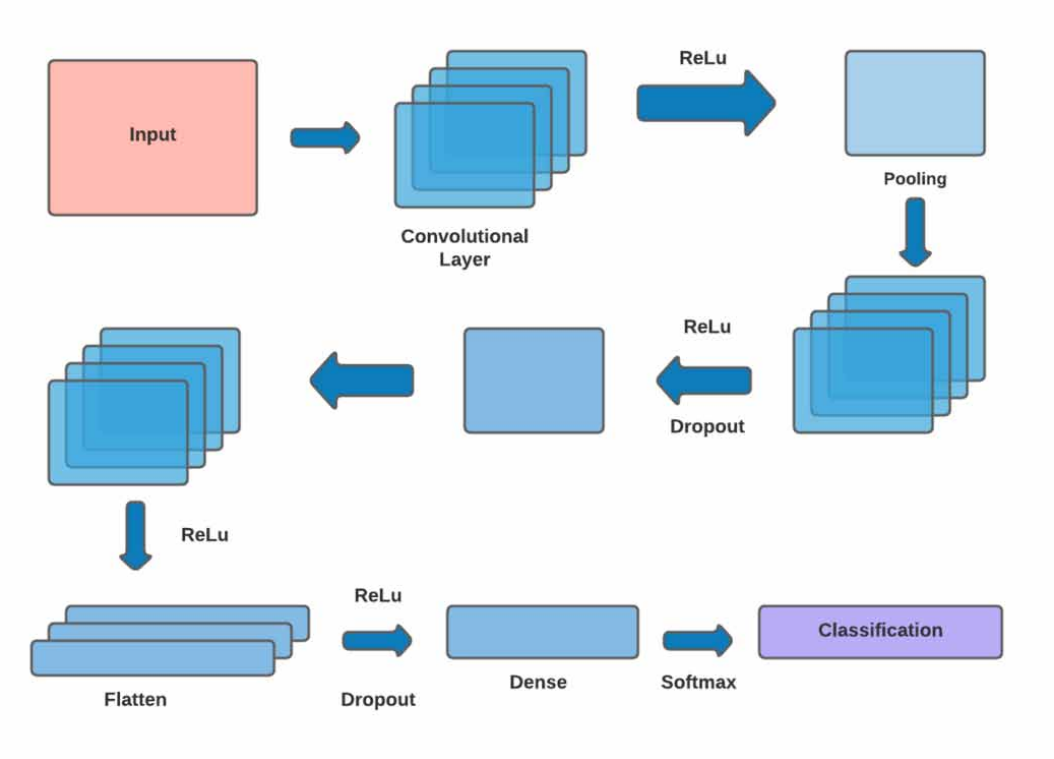
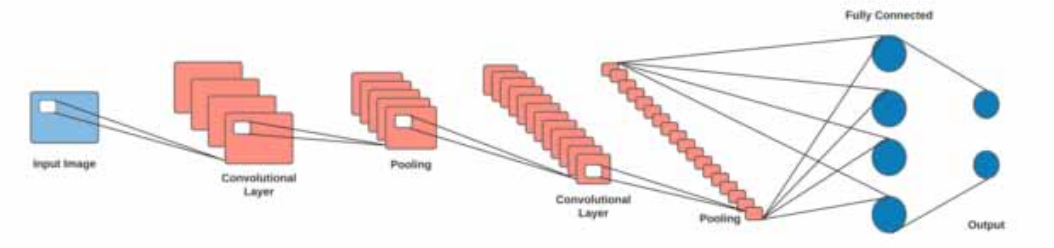


Figure 3. Architecture of a basic CNN



as seen in some of the state-of-the-art deep learning models. The model is optimized for multiclass classification for better accessibility in terms of performance and ease of use.

MATERIALS AND METHODS

Dataset

The images dataset has been collected from various sources such as Kaggle, IEEE Dataport, and manually compiled images (Abir et al., 2021, Popescu et al., 202, Li et al., 2021). The dataset has been divided into two sets i.e., training and testing sets. The training set consists of a total of 1200 images whereas the testing set consists of a total of 300 images. Bosets contain images of different

Table 1. Literature review

Author / Reference	Algorithm/Model	Application/Work
(Malliga et al., 2020)	CNN and AlexNet	A system that can classify three skin diseases: Melanoma, Nevus, and Seborrheic Keratosis, with an accuracy of 70% for CNN and 80% for AlexNet.
(Patil et al., 2020	KNN and K-means	Several filters like grayscale, noise and cropping have been used to extract the features of the images.
(Hashmani et al.,2021)	CNN	A single-instance optimized CNN model has been proposed and tested on a publicly available ISIC 2019 dataset of skin cancer. The system has achieved an accuracy of 95.6%.
(Dutta et al.,(2021)	DCNN	A Deep Convolutional Neural Network (DCNN) and transfer learning-based integrated system tested on the ISIC 2017 skin cancer dataset, including Melanoma, Seborrheic Keratosis, and Nevus with an average precision of 0.73, recall of 0.87, and F1-score of 0.74.
(Ayana et al., 2022)	MSTL	A Convolutional neural network (CNN) and with multiple optimizer system for training various ultrasound images to identify breast cancer.
(Junayed et al., 2019)	AcneNet	AcneNet can classify several types of acne lesions with an accuracy of 99.4% for one class, and 94% for the rest of the classes with a high recall & precision score.
(Kumar et al., 2016)	ML-CV Based Model	Machine learning and computer vision-based model to detect the type of skin disease. Computer Vision has been used to extract the features from the images. Machine learning has been used to identify the type of skin disease. The model has been tested on 6 types of skin disease. The final accuracy of the model has been observed as 95%.
(Malciu et al., 2022)	CNN	Using Deep learning based convolutional neural network algorithm on RCM images, Dermoscopy and Dermatopathology images for classifying skin dieses. Author got 87% accuracy.
(Bajaj et al., 2018)	ANN	The proposed approach is based on Two stage process for the classification of skin diseases. The disease-infected area has been converted into a feature vector for training the neural network. The model has achieved an overall accuracy of 90%.
(Bakheet et al., 2017)	SVM	An approach for melanoma skin cancer detection. It extracts HOG-based texture features from the skin affected area then 1D vector representation is plotted from the extracted features which are given to an SVM classifier. The classifier is trained and the model is generated for classification. The performance of the model in terms of sensitivity, specificity, and accuracy is 98.21%, 96.43%, and 97.32%.
(Wei et al., 2018)	SVM	An analysis method of vertical image segmentation to classify three common skin diseases. The model is based on SVM, in which a number of unnecessary variables can be minimized through image filtering, rotation, and the Euclidean distance transformation technique. The model achieved an accuracy of 85%, 90%, and 95% for the three diseases Herpes, Dermatitis, and Psoriasis respectively.
(Shen et al., 2018)	CNN	An automatic diagnosis method for facial acne that is based on CNN. To achieve the automatic acne diagnosis, there are two primary steps: (1) skin detection to pinpoint ROI. (2) seven-type classification of facial acne vulgaris. To achieve skin detection, the binary-classifier using CNN can extract features from input photos and classify them as skin or non-skin. A seven classifier with CNN is used to achieve the acne classification approach. CNN can extract features from input photos and categorize them into one of seven groups using the seven-classifier. The accuracy exceeds 81% for any class.

continued on following page

Table 1. Continued

Author / Reference	Algorithm/Model	Application/Work
(Patnaik et al., 2018)	InceptionV3, InceptionResNetV2, MobileNet	A system for three publicly available image recognition techniques namely InceptionV3, InceptionResnetV2, and MobileNet with modifications in skin disease application to predict the skin disease. The method employs pre-trained image recognizers that have been modified to recognize skin images. The models were tested on 20 diseases which gave an accuracy level of 88%.
(Kittigul et al., 2016)	SURF	A new method for extracting and classifying acne features. The Smooth Gaussian approach is used to pre-process the data. The system next performed BLOB identification and iterated using the Speeded Up Robust Feature (SURF) technique. Otsu Thresholding extract is applied to the discovered key locations, feature vectors are saved, and the database contains the training results. The correlation of nine features is statistically analyzed. The average accuracy achieved by the model is 73% with average sensitivity and precision of 78% and 90%.
(Alamdari et al., 2016)	Fuzzy-C-means and SVM	Proposed segmentation approaches for detecting acne lesions, as well as machine learning methods for distinguishing between acne lesions. Their findings revealed that two-level k-means clustering outperformed texture analysis. Also, k-means clustering, and "HSV model segmentation" reach an accuracy of 70%. In addition to this, the accuracy of differentiating acne scarring from active inflammatory lesions is 80% and 66.6% respectively for fuzzy-c-means and support vector machines.
(Shanthi et al., 2020)	AlexNet	This work is based on an automatic diagnosis of skin diseases based on computer vision. AlexNet architecture is used to classify four types of skin diseases namely Acne, Keratosis, Eczema herpeticum, and Utricaria. The model is trained on the learning rate of 0.01 which gives the final accuracy of 85.7%, 92.3%, 93.3%, and 92.8% respectively for the skin diseases Acne, Keratosis, Eczema herpeticum, and Urticaria. One of the key features of the proposed work is the vast image features generated by the Convolutional layer of the architecture are used in the final layer of the neural network for classification.
(Hammad et al., 2021)	CNN	This is an end-to-end CNN model with only one stage to detect Myocardial Infraction (MI) from input signals. The proposed work achieved an overall accuracy, precision, F1-score and recall value of 98.84%, 98.31%, 97.92%, and 97.63 respectively using focal loss. Without using focal loss, this model achieved an overall accuracy of 89.72%, a precision of 88.52%, a recall of 81.11% and F1 score of 83.02%.
(Sedik et al., 2022)	CNN and ConvLSTM	A COVID-19 detection system based on deep learning on the dataset of X-ray images and CT images with accuracy of 100% and F1-score of 100% in some cases.
(Li et al., 2019)	CNN	A mathematical approach that recognizes faces by comparing the original pixel blocks of face images using Macropixel comparison approach which is based on two features i.e., deep overlap and weighted filter.
(Wu et al., 2019)	CNN	Five mainstream CNN structures like Resnet50, Inception V3, Densenet-121, Xception, Inception-Resnet V2 is used for the diagnosis of clinical images of facial skin diseases.
(Kshirsagar et al., 2022)	MobileNetV2 and LSTM	A skin classification system is developed using MobileNetV2 and LSTM. The accuracy in skin disease prediction is the main contribution of this work. It gives the optimal efficiency in storing complete state information for exact predictions.
(Tripathi et al., 2020)	MCNN	A deep learning based method to detect COVID-19 cases using X-ray images of the chest. The method obtained 98.25% accuracy, 98.49% precision, 98% sensitivity, 98.50% specificity, and 98.25% F1 score.

dimensions and age groups for each class. All the images of the dataset are in PNG format. The dataset occupies 139 MB of system space.

Table 2. Limitations of existing work

Algorithm/Model	Limitation
CNN and AlexNet (Malliga et al., 2020)	1. Classification accuracy is low. Which is 70% and 80% respectively for CNN and AlexNet. 2. Network layers are not well tuned and optimized.
KNN (Patil et al., 2020)	1. Classification accuracy is minimum. For Acne skin disease, it gives only 79.1% accuracy. 2. The model has been trained on low image quality and feature combinations. 3. Network layers are not well tuned which affect the accuracy.
DCNN (Dutta et al., 2021)	1. Network layers are not standardized as required. 2. Hyper-parameter is required additional tuning with more related augmentations.
MSTL (Ayana et al., 2022)	1. Limitation in parameters such as optimizer, pre-trained models. 2. Require highly balanced and large dataset for going deep and correctly identification of disease.
AcneNet (Junayed et al., 2019)	1. Network architecture is not well structured. 2. Number of layers need to be optimized to improve the performance upon the current level.
MobileNet V2–LSTM (Kshirsagar et al.,2022)	A major difference is observed between training and testing accuracy. The accuracy during training was 86.57 and in testing, it reduced to slightly under 80%.

The description of the training and the testing set is shown in Table 3. The training set has 400 images of Acne and Rosacea, 400 images of Melanoma, and 400 images of other skin-related diseases. The testing set includes 100 images of Acne and Rosacea, 100 images of Melanoma, and 100 images of other skin-related diseases. There are 3 classes in the dataset, that are, Class 1 (Acne or Rosacea), Class 2 (Melanoma), and Class 3 (Other Skin diseases). Out of 1500 images, 1200 images have been used for training the model and 300 images have been used for testing the model.

The different dimensions of the image dataset have been shown in Table 4. The dimensions are given in pixel format. The minimum and maximum widths and height for Class 1 (Acne and Rosacea) are 100, 2576, 100 and 1932 pixels respectively. For class two (Melanoma) images, minimum and maximum widths are 720 and 720 pixels respectively. At the same time, the minimum and maximum heights are 481 and 596 pixels respectively. In Class 3 (Other Skin diseases) the minimum and

Table 3. Dataset Distribution

Class	Training images	Testing images
Acne & Rosacea	400	100
Melanoma	400	100
Other Skin diseases	400	100
Total	1200	300

Table 4. Dataset Distribution

Class	Minimum Width	Maximum Width	Minimum Height	Maximum Height
Acne and Rosacea	100	2576	100	1932
Melanoma	720	720	481	596
Other Skin diseases	100	1024	100	1370

maximum width of images are 100 and 1024 pixels respectively and minimum & maximum heights are 100 and 1370 pixels respectively.

Some sample images of Acne, Rosacea, Melanoma, and other skin-related diseases are shown in Figure 4. Such type of images has been used to train the proposed model.

Proposed Methodology

Architecture of XCNN

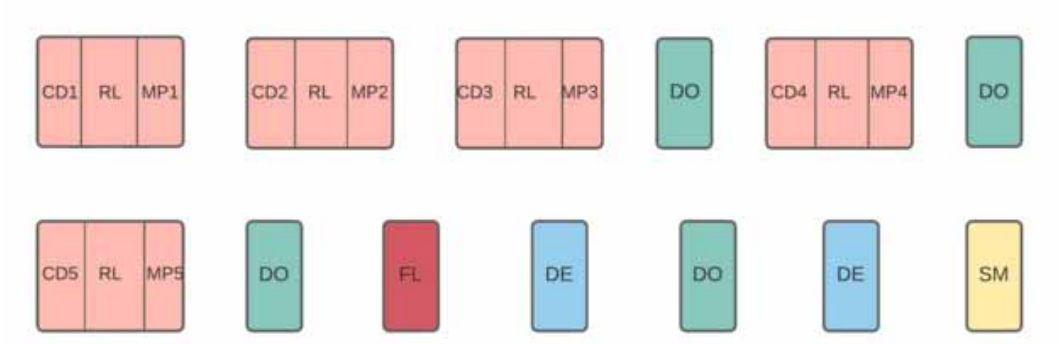
The XCNN layers used in the proposed method include five convolutional layers where the ReLU activation function and max-pooling layer have been stacked after each convolutional layer. After the third, fourth, and fifth convolutional layers, a dropout layer has been used. In the end, the softmax activation function was used. The sequence of the layers in the proposed method has been shown below with the following nomenclature. Here CD is the Convolutional 2D layer, RL is Rectified Linear Unit activation function, MP is the max pooling layer, DO is the dropout layer, FL is the flatten layer, DE is the dense layer and SM is the Softmax activation function. Figure 5 represents the sequentially stacked layers.

CD1-RL-MP1-CD2-RL-MP2-CD3-RL-MP3-DO-CD4-RL-MP4-DO-CD5-RL-MP5-DO-FL-DE-DO-DE-SM

Figure 6 shows the XCNN architecture. The input image has been processed via the convolutional layer, represented by Conv2D, where the image's features are extracted at different levels and layers are separated. The image's retrieved features are then supplied to the max-pooling layer, as represented. The features extracted from the convolutional layer are kept in that layer in a tiny matrix created by marking the matrix cell with the greatest value of the kernel matrix when superimposed on the Conv-layer matrix. This method is repeated with the number of features extracted from the previously-stored

Figure 4. Acne, Rosacea, Melanoma, Other Skin diseases (left to right) (Abir et al., 2021, Popescu et al., 2022, Li et al., 2021)

Figure 5. Sequence of layers used in the proposed model



layer with only a small change. After that, the dropout layer is applied when the feature extraction is completed and greater loss is noticed even after MaxPool is used. The two-dimensional MaxPool layer is flattened into a single column matrix form, and the flatten layer has been given a dense layer. In the final layer for classification, the Softmax activation function is used, and the highest percentage in which the image matches is recorded, and the image is predicted to be belonging to that class.

Layers and Parameters of XCNN

The parameters of convolutional and dense layers used in the proposed method are shown in Table 5. The output shape of the convolutional layer of the XCNN is a 4D array where the batch size is the same as the input batch size. The other three dimensions of the image might be changed depending upon the parameters of padding, filter, and kernel size used. The output shape is shown in the second column of the table. In output shape, the dimensions are basically height, width, and output filters. In XCNN, each layer consists of two types of parameters: weights & biases. This gives the total number of trainable parameters which is the sum of all weights and biases.

Proposed Algorithm

```
Algorithm 1: XCNN training algorithm
Convolution 2D: CD
Max-pooling: MP
img_width: a
img_height: b
1. Set a, b ¬ 200
2. Set the path for the training set and validation set
3. If keras.image_data_format ¬ 'channels_first' then
        input_shape ¬ (3, a, b)
   else
        input_shape ¬ (a, b, 3)
```

Figure 6. XCNN Architecture

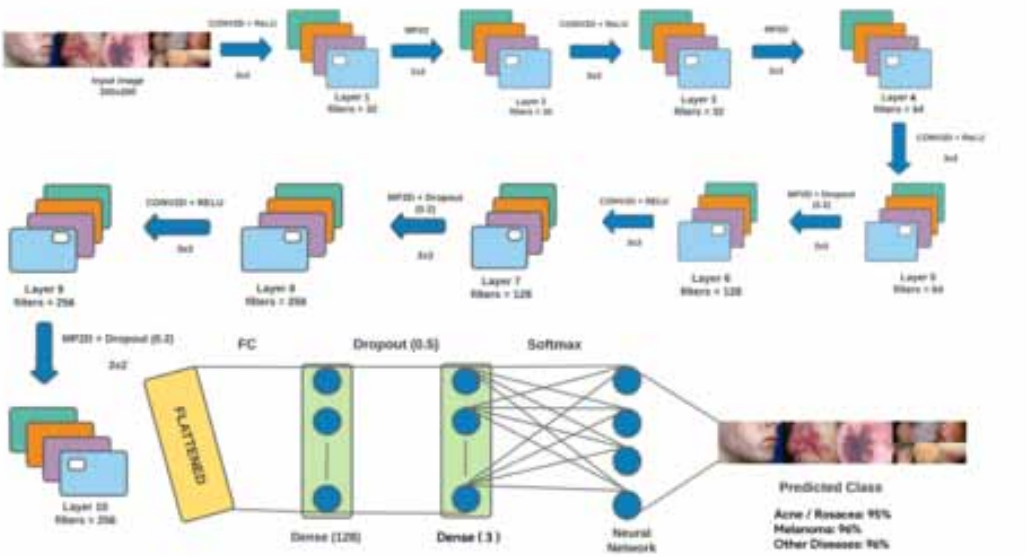


Table 5. XCNN Layers and Parameters

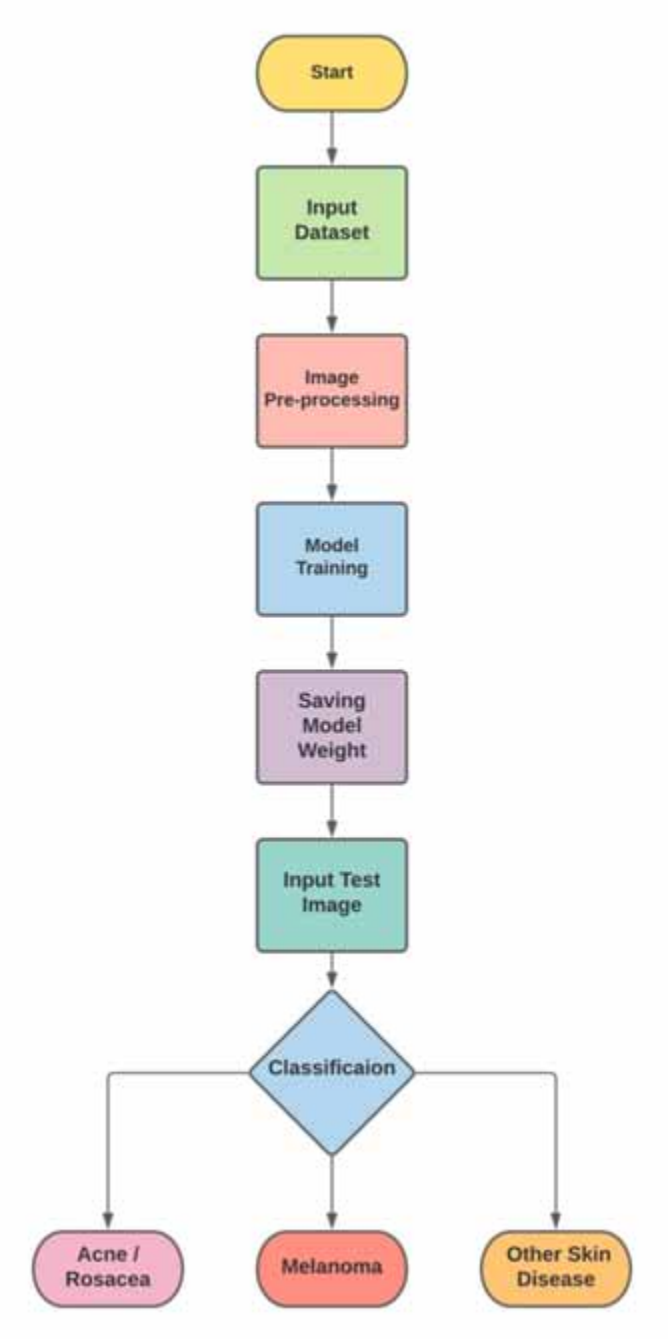
Layer (type)	Output Shape	Trainable Parameters
conv2d (Convolutional)	198, 198, 32	896
conv2d_1 (Convolutional)	97, 97, 32	9,248
conv2d_2 (Convolutional)	46, 46, 64	18,496
conv2d_3 (Convolutional)	21, 21, 128	73,856
conv2d_4 (Convolutional)	8, 8, 256	295,168
Dense	128	524,416
Dense	3	387

```
4. training ¬ ImageDataGenerator()
   testing ¬ ImageDataGenerator()
5. train_generator ¬ training.flow_from_directory()
   validation_generator ¬ testing.flow_from_directory()
6. Initialize XCNN model:
Apply Convolutional 2D operation (CD1) to the input
Apply Max-pooling (MP1)
Apply Convolutional 2D operation (CD2)
Apply Max-pooling (MP2)
Apply Convolutional 2D operation (CD3)
Apply Max-pooling (MP3)
Apply Dropout (0.2)
Apply Convolutional 2D operation (CD4)
Apply Max-pooling (MP4)
Apply Dropout (0.2)
Apply Convolutional 2D operation (CD5)
Apply Max-pooling (MP5)
Apply Dropout (0.2)
Fully connection
7. Training model:
model. fit(train_ generator, steps_per_epoch, epochs,
validation_data = validation generator, validation_steps)
model.save_weights()
8. Output: XCNN model
Algorithm 2: Classification of the Input Image
1. Set the path to the input image
2. Output ¬ XCNN model weight
3. Disease classification ¬ Output
```

Flowchart of the Proposed System

The flowchart of the proposed system XCNN is shown in Figure 7. The proposed method firstly loads the dataset and then performs feature extraction from the dataset. After the process of extraction is done then it saves the weight file which is later used for the classification of skin disease when an image is given as input to the model.

Figure 7. Flowchart of the proposed system



EXPERIMENTAL WORK AND RESULT ANALYSIS

A graph of accuracy on training and validation datasets over training epochs is shown in Figure 8. The number of epochs is represented on the X-axis of the graph and the Y-axis represents the accuracy value of the graph. After ten epochs, the model gives an accuracy of 85.36%, and validation accuracy

of 86.16%. At twenty epochs, the model accuracy is 88.12%, and the validation accuracy is 89.29%. At thirty epochs, the model accuracy is observed as 90.94% and validation accuracy as 91.52%. At fourty epochs, the model accuracy is 92.01% and validation accuracy is 93.30%. The model has achieved an accuracy of 95.67% with a validation accuracy of 94.86% at 50 epochs.

A graph of loss on training and validation datasets over training epochs is shown in Figure 9. The number of epochs is represented on the X-axis of the graph and the loss value is placed on the Y-axis of the graph. After 10 epochs, the loss value of the model is 38.54% with a validation loss of 36.48%. At 20 epochs, the value of the model loss is 29.52% with a validation loss of 26.61%. After 30 epochs, the model loss is 23.13% and a validation loss of 25.37%. The model loss value has been 22.44% and the validation loss is 21.29% at 40 epochs. After 50 epochs the loss value of the model is 15.81% and the loss value for validation is 24.08%.

Figure 8. Model accuracy

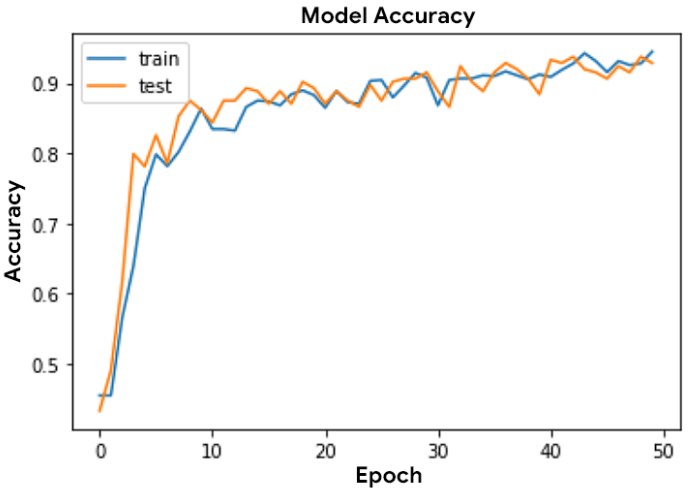
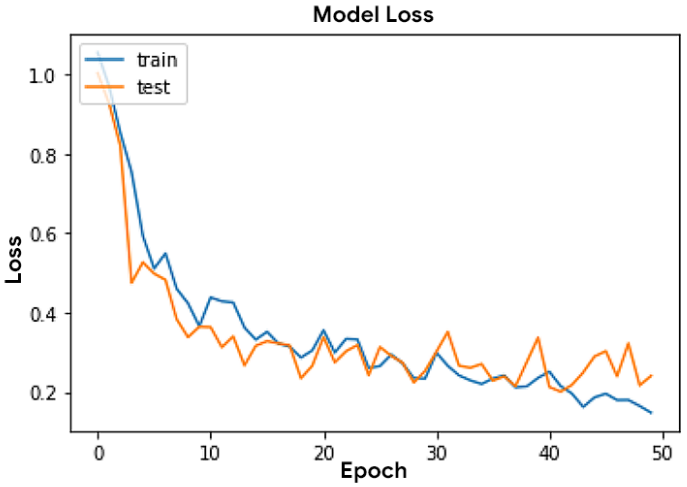


Figure 9. Model Loss



Confusion Matrix

A confusion matrix (C) is an N x N matrix that is used to evaluate the performance of a classification model, where N denotes the number of target classes. The confusion matrix compares the actual target values to the predicted values of the model. This provides a comprehensive picture of how well the classification model is working and the kind of errors or misclassification in the model. The confusion matrix generates the prediction in a summarized format with a total number of correct predictions and incorrect predictions. The scheme of the confusion matrix is shown in Figure 10.

True positive (TP) - The predicted value matches with the actual value which is true and the model predicted false.
True Negative (TN) - The predicted value matches the actual value which is false and the model predicted true.
False positive (FP) - The predicted value is falsely predicted. The actual value is false but the model predicted true.
False negative (FN) - The predicted value is falsely predicted. The actual value is true but the model predicted false.

A multi-class confusion matrix is different from a binary confusion matrix. The multi-class confusion matrix has N number of rows and a column where N is the number of classes. A multi-class confusion matrix is shown in Figure 11.

The elements of the confusion matrix for each class are shown in equations (1), (2), (3), and (4). TP is True Positive, FP is False Positive, FN is False Negative, TN is True Negative, C is confusion matrix and index "i" is a reference to each class (Wang et al., 2022).

Figure 10. Confusion Matrix Scheme

	Actual Positive	Actual Negative
Predicted Positive	True Positive	False Positive
Predicted Negative	False Negative	True Negative

Figure 11. Multi – Class confusion matrix

$$C = \begin{array}{c} \\ \text{Actual} \end{array} \overset{\text{Classifed}}{\begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \\ c_{n1} & & c_{nn} \end{bmatrix}}$$

$$TP_i = C_{ii} \text{ ----------} \quad (1)$$

$$\text{FP}_i = \sum_{l=1}^{n} C_{\text{li}} - \text{TP}_i \text{----------} \quad (2)$$

$$\text{FN}_i = \sum_{l=1}^{n} C_{\text{il}} - \text{TP}_i \text{----------} \quad (3)$$

$$\text{TN}_i = \sum_{l=1}^{n} \sum_{k=1}^{n} C_{\text{lk}} - \text{TP}_i - \text{FP}_i - \text{FN}_i \text{----------} \quad (4)$$

In Figure 12, the format of the confusion matrix for the proposed model is shown. The first column and first row are used for Acne/Rosacea class. The second column and second row denote the Melanoma class. The third row and third column represent other skin-related disease classes.

The True Positive, False Positive, False Negative and True Negative for each class are calculated as shown in Table 6. Cell "i" denotes each cell of the multi-class confusion matrix. The "i" denotes the cell number which is shown in Fig 12.

The Multi-Class Confusion matrix for the proposed model is shown in Table 7. Since there are 3 classes in the proposed method therefore a 3 x 3 confusion matrix has been obtained. The diagonal cells of the confusion matrix represent the number of correct predictions made by the proposed method. The non-diagonal cells denote the wrong predictions made by the proposed model.

Evaluation Technique/Classification Report

The classification report of the proposed model includes the precision, recall, and F1 score of each class (Tripathi et al., 2020). The higher the precision and recall value the better the model is in terms of accuracy. The support in the classification report denotes the number of test images.

Precision - It represents how many of the cases that were correctly predicted turned out to be true. The formula to calculate precision is denoted in the equation (5).

$$\text{Precision} = \frac{TP}{TP + FP} \text{ --------- eq} \quad (5)$$

Recall – It explains how many of the actual true cases the model is able to properly predict. Equation 6 denotes the formula for recall calculation. (6).

$$Recall = \frac{TP}{TP + FN} \text{ --------- eq} \quad (6)$$

F1 – Score – The weighted average of Precision and Recall is the F1- score. As a result, this score considers both false positives and false negatives. The formula to calculate the F1-score is shown in equation (7).

Figure 12. Multi – Class confusion matrix for the proposed model

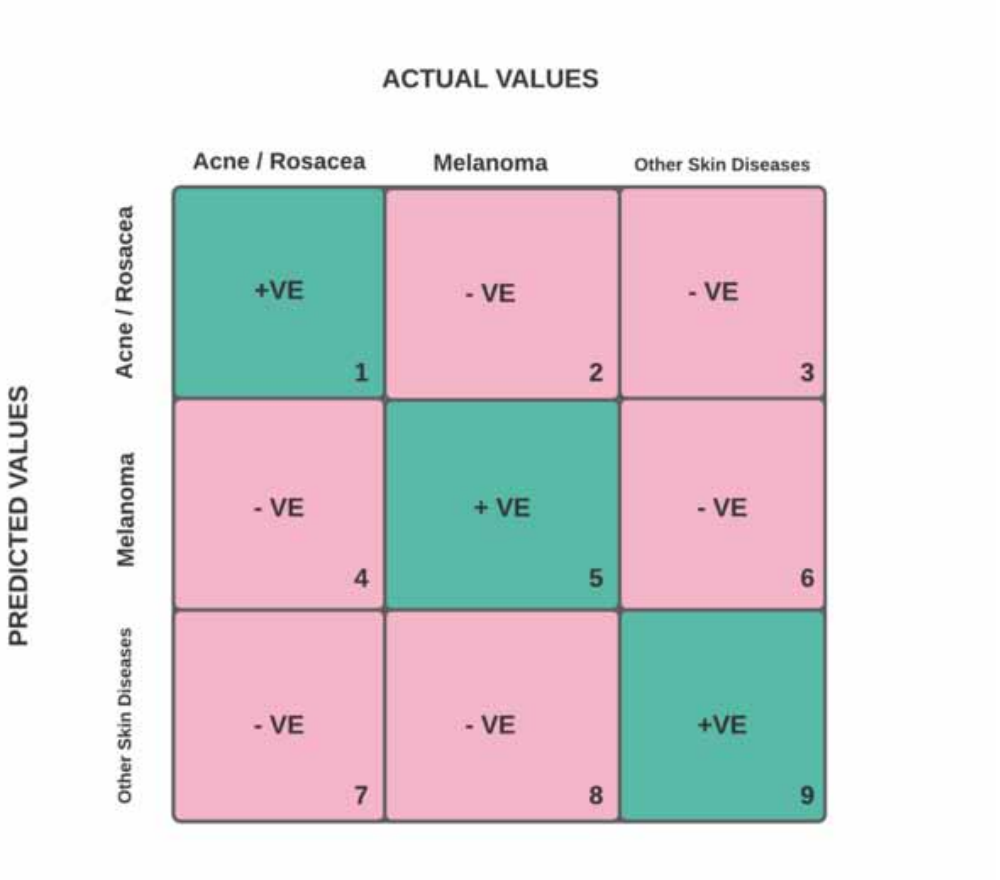


Table 6. Confusion matrix parameters used for each class

ACNE / ROSACEA	MELANOMA	OTHER SKIN DISEASES
TP = $Cell_1$	TP = $Cell_5$	TP = $Cell_9$
FP = $Cell_2 + Cell_3$	FP = $Cell_4 + Cell_6$	FP = $Cell_7 + Cell_8$
TN = $Cell_5 + Cell_6 + Cell_8 + Cell_9$ FN = $Cell_4 + Cell_7$	TN = $Cell_1 + Cell_3 + Cell_7 + Cell_9$ FN = $Cell_2 + Cell_8$	TN = $Cell_1 + Cell_2 + Cell_4 + Cell_5$ FN = $Cell_3 + Cell_6$

Table 7. Confusion Matrix for the proposed model

		True Class		
		Acne/Rosacea	**Melanoma**	**Other Skin diseases**
Predicted Class	**Acne/Rosacea**	95	2	3
	Melanoma	3	96	1
	Other Skin diseases	2	2	96

$$\text{F1} - \text{Score} = 2 \times \frac{\left(Recall \times \ Precision\right)}{\left(Recall + \ Precision\right)} \text{--------- eq} \tag{7}$$

Support - Support is the number of actual occurrences of the class in the specified dataset. It is the number of test images that are used to categorize the input images.

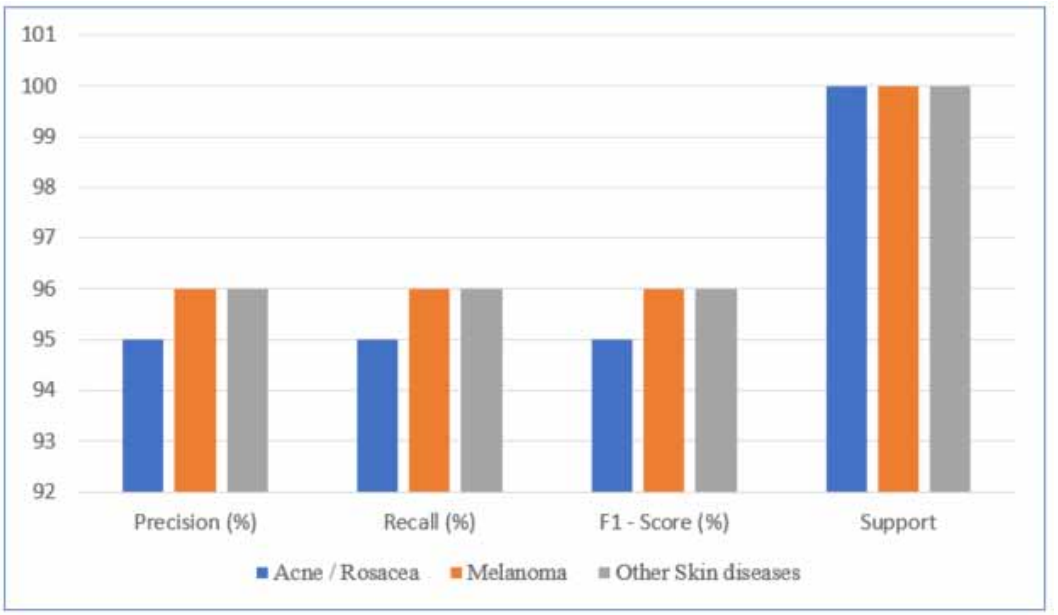
The classification report for the proposed method which describes the precision, recall, F1-score, and support is shown in Table 8 and Figure 13. The precision, recall, F1-score, and support of each class are given in the table. In the classification report, the class column denotes the name of the class. The precision column denotes the precision value for that particular class. The recall column denotes the recall value of each class in their respective row. The F1-score column denotes the F1-score value of each class. The support denotes the number of test images that are used for the classification of each class.

The proposed model can effectively classify the three different skin-related disease classes with an accuracy of 95.67%. The classification report has displayed a per-class representation of the key classification metrics such as precision, recall, F1 – score, and support.

Table 8. Classification report

Class	Precision (%)	Recall (%)	F1 - Score (%)	Support
Acne / Rosacea	95	95	95	100
Melanoma	96	96	96	100
Other Skin diseases	96	96	96	100

Figure 13. Classification Report Graph



EXPERIMENTAL RESULTS

The accuracy of XCNN with other existing algorithms (models/methods) is given in table 9. The table shows comparative accuracy of 70%, 80%, 81.92%, 95.60%, 86.11%, 87% and 95.67% respectively for CNN (Malliga et al., 2020), AlexNet (Malliga et al., 2020), KNN (Patil et al., 2020), Model (Single-instance optimized CNN) (Hashmani et al., 2021), AcneNet (Junayed et al., 2019), DCNN (Dutta et al., 2021), and XCNN. The results obtained by XCNN is more accurate and gives better result as compared to other state-of-the-art algorithms for skin disease classification.

The graphical representation of the algorithm's accuracy is shown in Figure 14. In the graph, the algorithm names are represented horizontally on the X-axis of the graph, and the accuracy percentage values are represented vertically on the Y-axis of the graph. The plotted graph shows the significance of XCNN in terms of accuracy. It also indicates how XCNN is better in performance in comparison to the other competitive algorithms.

Table 9. Accuracy of different algorithm

S. No.	Algorithm/Model	Accuracy (%)
1.	CNN (Malliga et al., 2020)	70
2.	AlexNet (Malliga et al., 2020)	80
3.	KNN (Patil et al., 2020)	81.92
4.	Model (Single-instance optimized CNN) (Hashmani et al., 2021)	95.60
5.	AcneNet (Junayed et al., 2019)	86.11
6.	DCNN (Dutta et al., 2021)	87
7.	Proposed (XCNN)	**95.67**

Figure 14. Graphical representation of the accuracy of different algorithm

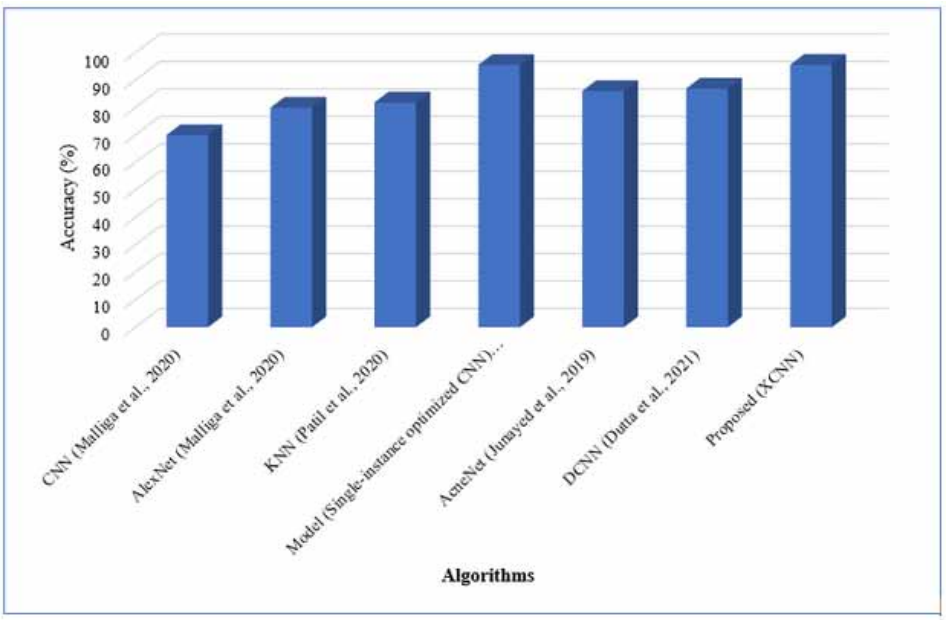


Table 10 depicts the comparative results of the precision value for Acne skin disease. In the table, three algorithms i.e., AIA (Seité et al., 2019)AcneNet (Junayed et al., 2019), and XCNN have been compared based on their precision values. It is found that the proposed XCNN has got a 95% precision value while AIA and AcneNet have got 84% and 91.67% precision values respectively. Thus, as per the given precision values in the table, the XCNN has improved by 11% over AIA and 3.33% over AcneNet respectively. The gap in precision value with XCNN for AIA is large as compared to AcneNet. While the performance of AcneNet is comparable to XCNN at some level but still XCNN is better than AcneNet in terms of precision. Hence, based on the results, it is concluded that the proposed XCNN provides the highest precision value for the Acne skin disease class.

The graph of the precision values obtained by the three algorithms namely AIA, AcneNet, and XCNN for the Acne skin disease is plotted in Figure 15. In the graph, the X-axis shows the name of the algorithms and the Y-axis shows the precision percentage of these algorithms. As per the precision value shown in the graph, the XCNN has gained the maximum precision value which is the highest of other algorithms.

The recall percentage value for the three algorithms is shown in table 11. The recall value is given for Acne skin disease. The XCNN has achieved 95% recall value while the other two algorithms AIA and AcneNet has got 84% and 89.91% recall value respectively. The overall improvement of XCNN over AIA and AcneNet are 11% and 5.09% respectively. Thus, the results show that the XCNN has gained remarkable improvement over its competitive algorithms.

In Figure 16, the graphical representation of the recall values for the Acne skin disease obtained by the XCNN, AIA, and AcneNet has been plotted. In the graph, the X-axis represents the algorithm

Table 10. Acne precision value of different algorithm

S. No.	Algorithm/Model	Disease	Precision (%)
1.	AIA (Seité et al., 2019)	Acne	84
2.	AcneNet (Junayed et al., 2019)	Acne	91.67
3.	Proposed (XCNN)	Acne	**95**

Figure 15. Graphical representation of the precision value of Acne obtained from the different algorithm

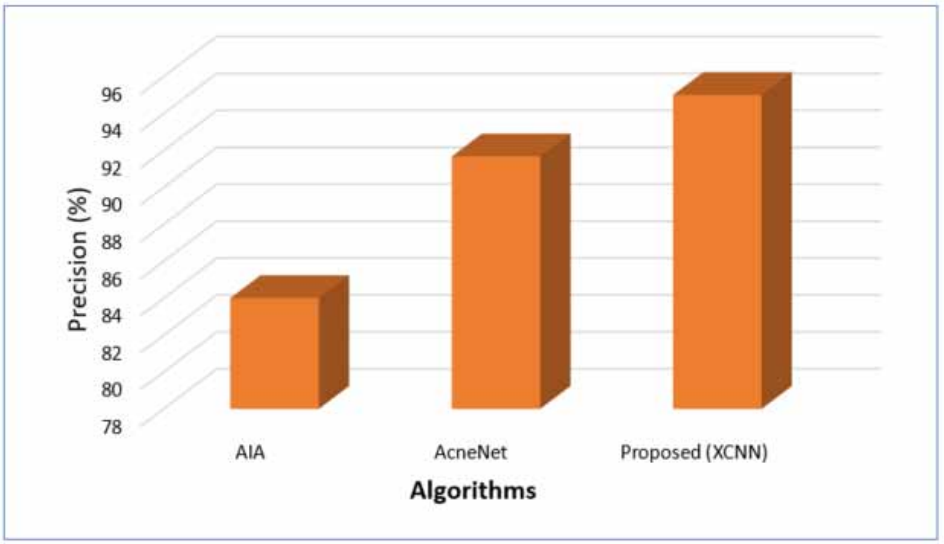


Table 11. Acne recalls value of different algorithm

S. No.	Algorithm/Model	Disease	Recall (%)
1.	**AIA (Seité et al., 2019)**	**Acne**	**84**
2.	AcneNet (Junayed et al., 2019)	Acne	89.91
3.	Proposed (XCNN)	Acne	**95**

names. The Y-axis represents the recall value percentage of the algorithms. After analysing the graph, it is observed that the XCNN has showed its efficiency over other algorithms. It has achieved the maximum recall value which can be clearly visualized in terms of gain.

The precision percentage value of four algorithms for Melanoma skin cancer disease are shown in Table 12. These algorithms are CNN, DCNN, Model (Single-instance optimized CNN), and XCNN. The precision value for these four algorithms is 29%, 53%, 95%, and 96% respectively. When observing these results, it is found that the XCNN performance is comparatively better and shows its efficiency in recognizing the Melanoma with acceptable precision value. The difference observed in the performance of the algorithms CNN, DCNN, and Model (Single-instance optimized CNN) as compared to XCNN are 67%, 43%, and 1% respectively. It is found that the difference between the result of CNN and XCNN is very large as compared to the other two algorithms. Only Model (Single-instance optimized CNN) has shown the minimum gap which is 1% less than the CNN. While other two algorithms have shown a large gap in comparison to XCNN in their performance which is 67% and 43% respectively for CNN and DCNN.

Figure 17 shows the graphical comparison of the performance of four algorithms such as CNN, DCNN, Model (Single-instance optimized CNN), and XCNN. The precision percentage value is shown on the Y-axis and name of the algorithms are shown on the X-axis. The graph indicates that the performance of CNN and DCNN is comparatively weak as compared to Model (Single-instance

Figure 16. Graphical representation of the recall value of Acne obtained from the different algorithm

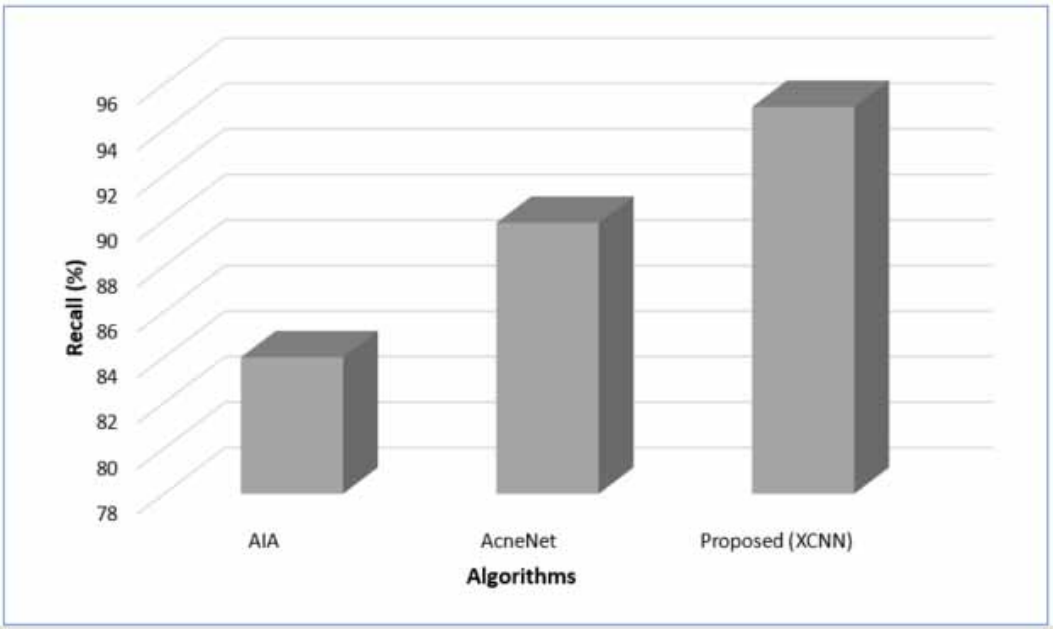


Table 12. Melanoma precision value of different algorithm

S. No.	Algorithm/Model	Disease	Precision (%)
1.	CNN (Malliga et al., 2020)	Melanoma	29
2.	DCNN (Dutta et al., 2021)	Melanoma	53
3.	Model (Single-instance optimized CNN) (Hashmani et al., 2021)	Melanoma	95
4.	Proposed (XCNN)	Melanoma	**96**

optimized CNN) and XCNN. While Model (Single-instance optimized CNN) and XCNN are performance-wise good to give a high precision value. Although, the difference in precision value between XCNN and Model (Single-instance optimized CNN) is 1%. But XCNN is more optimized and better than its comparative algorithms.

The recall percentage value of Melanoma is depicted in table 13. Four algorithms such as CNN, DCNN, Model (Single-instance optimized CNN), and proposed XCNN have been compared to show their respective results in the table. As compared to XCNN, the differences found in CNN, DCNN, and Model (Single-instance optimized CNN) are 67%, 34%, and 1% respectively. The difference percentage of CNN and DCNN is very high as compared to Model (Single-instance optimized CNN) with XCNN.

In Figure 18, the graphical representation of the recall percentage value for Melanoma of the following algorithms has been plotted. In the graph, the X-axis represents the different algorithm names. The Y-axis represents the recall percentage value of four algorithms. The graph shows that the performance-wise CNN and DCNN are weak in comparison to Model (Single-instance optimized CNN) and XCNN. While both algorithms (Single-instance optimized CNN) and XCNN are showing high recall values. But when both are compared to each, XCNN has found a 1% improved recall value

Figure 17. Graphical representation of the precision value of Melanoma obtained from the different algorithm

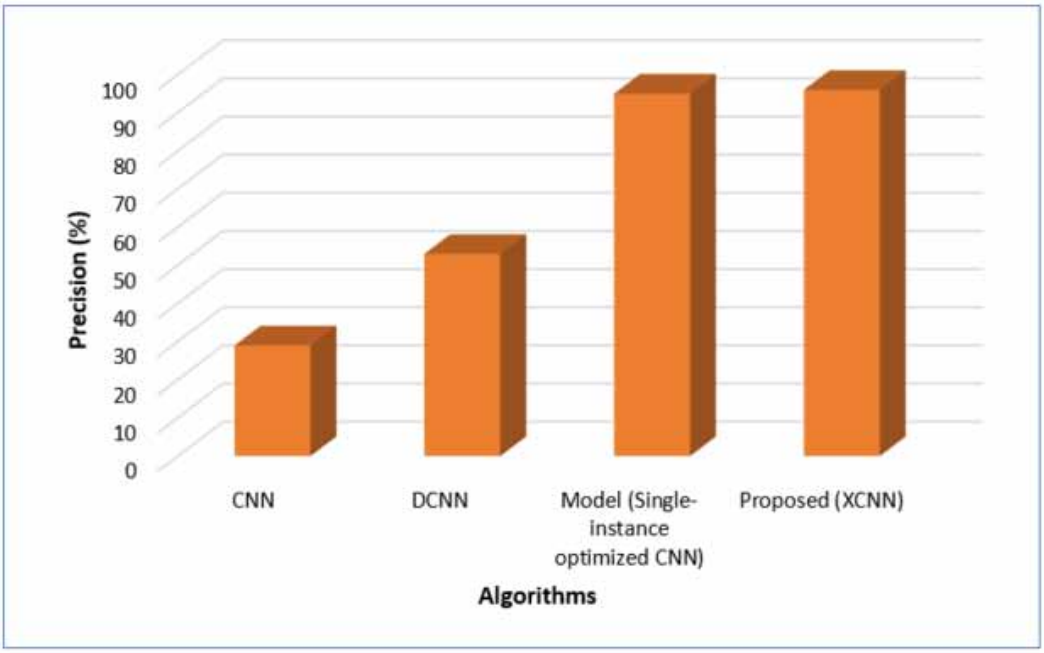


Table 13. Melanoma recall values for algorithms

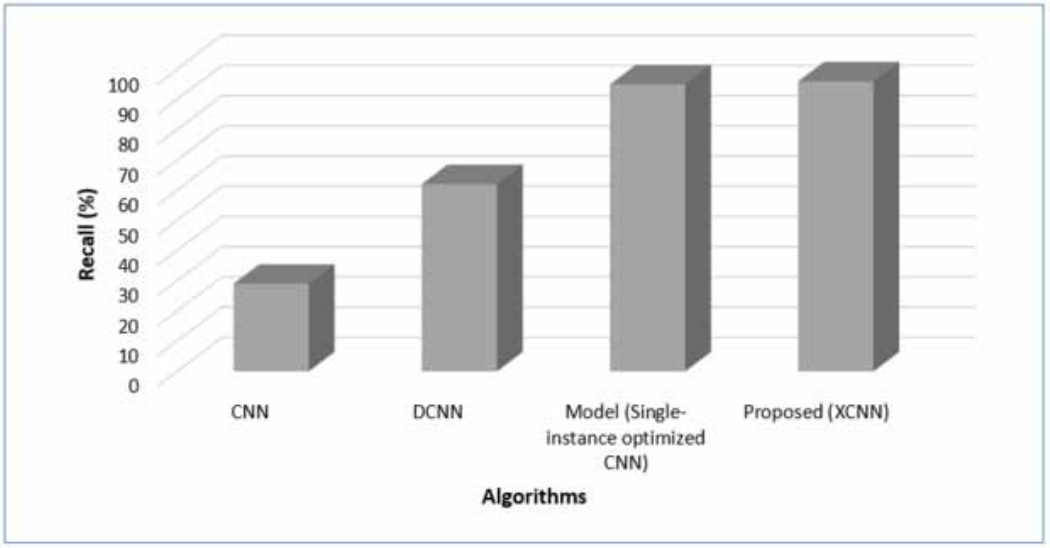
S. No.	Algorithm/Model	Disease	Recall (%)
1.	CNN (Malliga et al., 2020)	Melanoma	29
2.	DCNN (Dutta et al., 2021)	Melanoma	62
3.	Model (Single-instance optimized CNN) (Hashmani et al., 2021	Melanoma	95
4.	Proposed (XCNN)	Melanoma	**96**

over Model (Single-instance optimized CNN). That indicates that the XCNN is good at finding better recall values than the state-of-the-art algorithms which have been shown in the graph.

COMPARATIVE ANALYSIS

There are several state-of-the-art algorithms (models) for skin disease classification have been proposed in the literature. And every algorithm has its significance with respect to the disease classification. To check the performance of these algorithms some statistical and standardized parameters are given. Based on such parameters, a comparative analysis is shown in table 14. The graphical representation of the performance of the algorithms is given in Figure 19. In the table, three parameters i.e., accuracy, precision, recall, and eight algorithms are taken for the comparative analysis. The comparative results are shown with respect to different skin diseases. After deep observation, it is found that the performance of XCNN is exceptionally good as compared to other existing algorithms as shown in table 14 and Figure 19. CNN and AlexNet, proposed by (Malliga et al., 2020) are trained on three skin disease datasets i.e., Melanoma (439 images), Nevus (551 images) Seborrheic Keratosis (413 images), and classify these skin diseases. The accuracy, precision, and recall percentage value for CNN obtained by the authors are 70%, 29%, and 29%, respectively. While for AlexNet only the accuracy percentage value (80%) is mentioned. CNN has obtained 25.67%, 67%, and 67% respectively minimum values than XCNN for

Figure 18. Graphical representation of the recall value of Melanoma obtained for the different algorithm



accuracy, precision, and recall. While the difference in the Accuracy value of XCNN and AlexNet is 15.67. The KNN algorithm (Patil et al., 2020) is used in the identification of skin diseases which are Acne, Amyloidosis, Cherry-Angioma, Eczema Lids, and Halo-Nevus with the self-collected dataset. This algorithm has given 81.92% accuracy which is 13.75% lesser than the XCNN. A single-instance optimized CNN (Hashmani et al., 2021) is used on ISIC 2019 dataset to classify Melanoma skin disease. The algorithm has presented the accuracy, precision, and recall values 95.6%, 95%, and 95% respectively for the disease classification. The percentage value for all parameters given by this algorithm is very near to XCNN. However, the overall performance of the XCNN is satisfactory and even in this competitive analysis it has gained improved accuracy, precision, and recall values by 1.6%, 1%, and 1% respectively.

Dutta et al., 2021 mention that the Deep Convolutional Neural networks and transfer learning are used and tested on the publicly available IEEE International Symposium on Biomedical Imaging (ISBI) 2017 dataset. This algorithm has shown the accuracy, precision and recall value for the Melanoma skin disease. It has received 87% accuracy, 53% precision and 62% recall. It has been observed that the XCNN is 8.67%, 43%, 34% respectively higher percentage value than their proposed model "DCNN" for accuracy, precision and recall. An algorithm named "Artificial Intelligence Algorithm (AIA)" (Seité et al., 2019) is developed for the Acne skin disease analysis. They used to determine the severity of facial acne using the GEA scale. They worked on 5,972 images obtained from 1072 acne patients. They have received 84% precision value and 84% recall value for skin disease classification. Here, the XCNN has found same improvement of 11% for both parameters (i.e., precision & recall) over AIA. A Deep Residual Neural Network CNN model "AcneNet" (Junayed et al.,2019) is proposed for Acne skin disease classification. They trained and tested on five classes of Acne disease (i.e., Closed, Comedo, Cystic, Keloidalis, Open Comedo, and Pustular). The accuracy, precision and recall value for this algorithm is 86.11%, 91.67%, and 89.91% which is 9.56%, 3.33% and 5.09% respectively lesser value than XCNN in performance.

The use of optimized training layers in developing the model has a significant role in getting the optimal solution. Because the use of a smaller number of layers led to an inefficient model (less accurate: initially gives incorrect prediction) and more layers affect the model by increasing overall training time and also prediction. Thus, XCNN has taken all the necessities which is required for a good an optimized model.

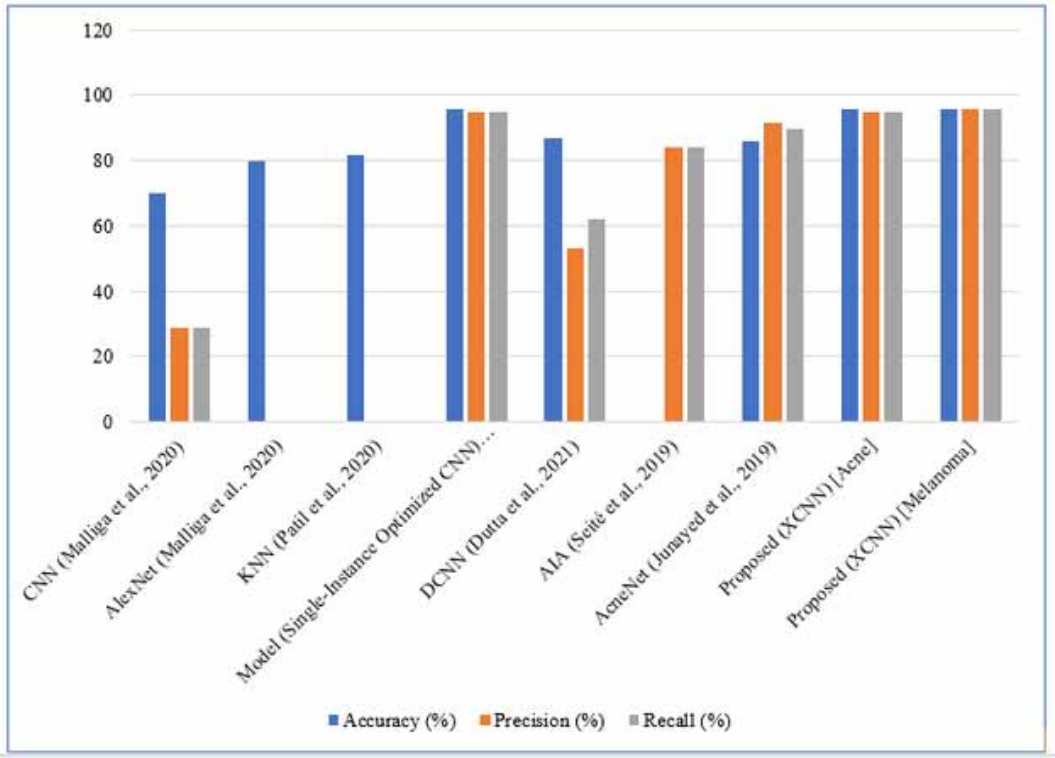
COMPARISON WITH RECENT RESEARCH WORK

In recent research work (Kshirsagar et al.,2022), the authors have developed a skin disease classification system. This system includes the combined approach of MobileNetV2 and LSTM. In their research

Table 14. Comparative Results on Different Parameters

Algorithm/Model	Accuracy (%)	Precision (%)	Recall (%)
CNN (Malliga et al., 2020)	70	29	29
AlexNet (Malliga et al., 2020)	80	-	-
KNN (Patil et al., 2020)	81.92	-	-
Model (Single-Instance Optimized CNN) (Hashmani et al., 2021)	95.6	95	95
DCNN (Dutta et al., 2021)	87	53	62
AIA (Seité et al., 2019)	-	84	84
AcneNet (Junayed et al., 2019)	86.11	91.67	89.91
Proposed (XCNN) [Acne]	**95.67**	95	95
Proposed (XCNN) [Melanoma]	**95.67**	96	96

Figure 19. Graphical comparative representation of the results obtained on different parameters for different algorithms



work, they have compared six other deep learning-based algorithms with the proposed "MobileNet V2–LSTM" which has been shown in table 15. In the table XCNN values have been also added to see performance on all statistical parameters. The visual representation of this comparative analysis is shown in Figure 20. In table 15, it can be observed that, performance of XCNN is compared with seven different algorithms (models). The XCNN shows the highly accurate results with accuracy 95.57(%), recall (96%), precision (96%), and F-measure (96%). After XCNN, MobileNet V2–LSTM is the second algorithm, whose performance is higher than rest of the algorithms. However, different factors may be responsible for this performance for other given models but high-error rate in pre-processing phase may be one of them.

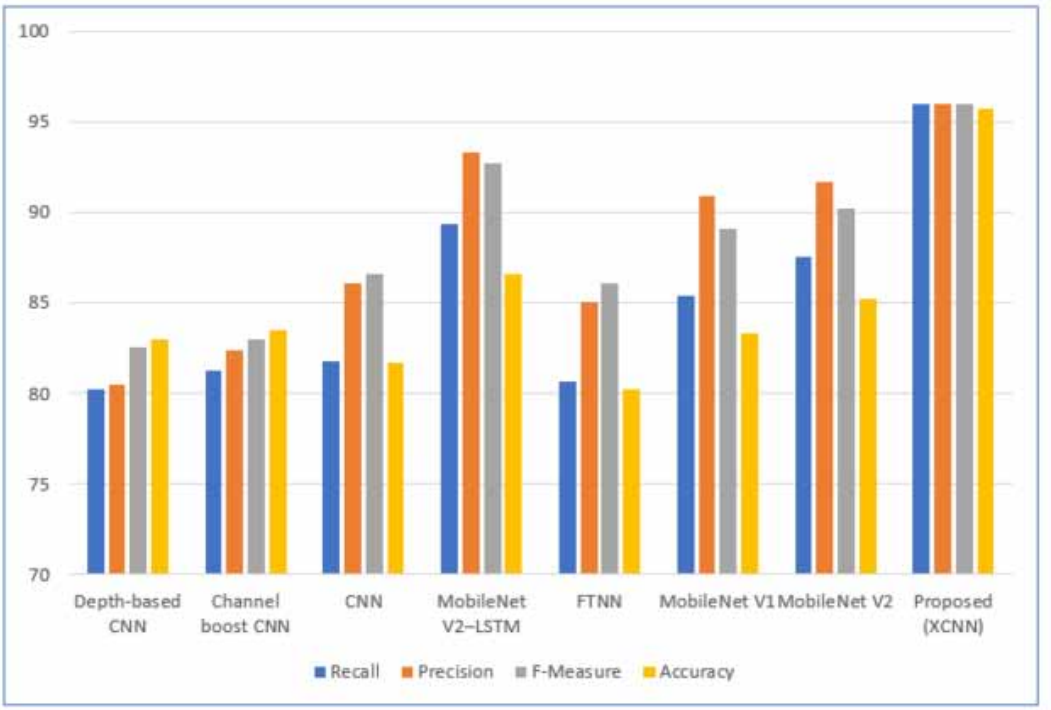
CONCLUSION

The body's largest and most distinctive organ is the skin. Blood arteries, lymphatic vessels, nerves, and muscles make up this organ, which allows it to sweat, sense the outside temperature, and defend the body. The skin not only serves as a sensory organ for the outside environment, but it also shields the body's internal organs and tissues from harmful substances, bacteria, pollution, and the sun's UV rays. Thus, the detection of skin diseases at an early stage is very significant to decrease the risk of spreading and growth. Traditional clinical procedure for the identification of skin disease is time-consuming and expensive for general public usage. Thus, using the image processing methodologies and deep learning techniques tends to save time and money. The feature extraction from the images holds a major part in the classification of the skin disease type. Taking all these things into consideration, the proposed model has been developed to detect and classify skin diseases with minimum effort and less computational resources. The results are very promising due to the enhanced performance

Table 15. Comparative Results on Different Parameters

Algorithm/Model	Recall	Precision	F-Measure	Accuracy
Depth-based CNN	80.23	80.49	82.56	82.93
Channel boost CNN	81.24	82.39	82.98	83.45
CNN	81.75	86.07	86.61	81.67
MobileNet V2–LSTM	89.34	93.34	92.68	86.57
FTNN	80.65	85.07	86.07	80.23
MobileNet V1	85.4	90.92	89.12	83.34
MobileNet V2	87.51	91.69	90.23	85.23
Proposed (XCNN)	96	96	96	95.67

Figure 20. Comparison with Recent Research Algorithms



on all statistical parameters as compared to other state-of-the-art techniques. By keeping the most recent timestamp data, the model increases prediction accuracy while being computationally efficient. The model is tuned specially for multi-classification with layers and parameters of a Convolutional Neural Network. The modified algorithm is trained on a structured image dataset. It is developed with enhanced accuracy, precision, recall, and F1 – score. Also, a minimum amount of time has been used to train the model. If any loss has been observed while training the model, then a dropout layer was used to reduce the loss and sustain the feature extraction optimally. The model has also been compared with a number of other conventional and recently released models. The suggested model outperformed others in classifying the skin illnesses, as shown in sections 5.3, 5.4, and 5.5. The model

accuracy graph shows that the model has achieved an accuracy of 85.36% at 10 epochs, 88.12% at 20 epochs, 90.94% at 30 epochs, and 91.52% at 40 epochs, and the best accuracy of 95.67% at 50 epochs. The overall accuracy of the proposed model is 95.67%. The recall, precision, and F1-score of the suggested model for Acne is 95%, for Melanoma is 96%, and for other skin diseases is 96%. The performance of the proposed model is satisfactory for three kinds of skin disease classification. While considering other types of skin diseases this model needs to be upgraded. The suggested model is not the replacement of the existing laboratory-based diagnostic techniques, but it may work as a support in their decision-making. In general, a laboratory-based diagnosis is always more reliable than a diagnosis based on visual symptoms.

FUTURE SCOPE

Further increase of the classes in the proposed work and large dataset which includes clear skin lesion images can be added. The model has gained maximum accuracy of 95.67% which can be further improved by a more configured and enhanced structured deep neural network. Some additions can also be made, such as creating a Graphical User Interface (GUI) web-based application for simply uploading the images or creating full-featured software with even more features and skin diseases. A portable version for mobile devices can also be developed so that it will be easier for the public to use.

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