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Multi-Class Skin Diseases Classification Using Hybrid Deep Convolutional Neural Network

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Abstract-There are many obstacles to accurate skin disease diagnosis and quick treatment. In this paper, we provide a multi-class skin disease categorization framework that incorporates a powerful convolutional neural network (CNN), MobileNet V2 (MNV2), and a LSTM (Long Short Term Memory) in order to increase the accuracy and dependability of diagnosis. The suggested approach makes use of LSTM's capacity to handle multi-class classification tasks and CNN's ability to automatically learn discriminative features from raw skin images. Multiple convolutional layers are followed by fully connected layers in the proposed hybrid CNN architecture. To improve gradient flow and lessen the vanishing gradient issue, it contains residual connections. Additionally, it integrates attention techniques to deliberately highlight informative areas in the skin images, improving the network's ability to discriminate. The suggested solution outperforms previous methods with an accuracy greater than 87% and makes use of the HAM10000 dataset to do so. Additionally, it displays exceptional stability in quickly locating the damaged area while using almost half as much computational resources as the traditional MobileNet model. This results in substantially less computational work being required without sacrificing classification speed or accuracy.

Keywords: *Deep Convolution Neural Network, Skin Diseases, Long Short-Term Memory, Image processing, Multi-class diseases*

I. Introduction

Skin conditions can be caused by a number of things, including bacterial colonization, allergic reactions, microbial imbalances, fungal infections, or aberrant pigmentation [1]. Because some skin conditions can develop into malignancies and even become chronic, prompt treatment is crucial to limiting their growth and spread [2].

The need for research centered on utilizing imaging technology to recognize and treat various skin disorders is rising in this environment. The symptoms of many skin conditions can be difficult to adequately diagnose, which can cause delays in treatment that can extend for several months. To enable early identification and assessment of the impact of various skin illnesses, methods and techniques are being developed. This will facilitate quick and efficient interventions.

Previous studies in computer-aided classification for dermatological applications frequently lacked the ability of medical professionals to generalize. This restriction is explained by a lack of information and the importance placed on standard tasks, particularly ceroscopy, which calls for the use of a superficial microscope to examine the skin. However, computer-assisted diagnosis can quickly and accurately classify skin conditions, allowing for the prescription of treatments based on the

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patient's symptoms. [3] In order to effectively identify skin disorders employing supervisory methodologies and lower the expense of diagnostics, this work proposes a reliable mechanism. The development of sick growth is evaluated using a grey-level co-occurrence matrix. In order to thoroughly evaluate anomalies, which improves treatment outcomes and lowers drug costs, the accuracy of the diagnosis is essential.

Data-driven diagnosis is essential due to the variety of skin diseases and the scarcity and unequal distribution of skilled dermatologists. The precision and speed of skin disease diagnosis have substantially increased because to recent developments in laser and photonics-based medical technologies. The price of such diagnoses continues to be a barrier, though. Using picture and data inputs, deep learning models [4], [7] have shown to be effective at classifying illnesses. It is essential to correctly categorize the condition. By automatically collecting pertinent features from input data and adjusting to shifting problem domains, deep learning models provide answers. Even with minimal computational complexity, these models effectively identify patterns in both exposed and unexposed data. In the suggested work, the authors used a deep learning model to diagnose different types of skin diseases based on photographs of the affected areas.

The key objective of this paper is to introduce a cutting-edge method for precise skin disease categorization utilizing images taken with mobile devices, specifically the combination of CNN, MobileNet V2 and LSTM. The practical application of this approach is the creation of a mobile application that enables users to take pictures of the skin's affected area, which are then utilized to identify the type of skin illness. Due to its computational efficiency and suitability for deployment on lightweight computational devices, the authors selected the MobileNet V2 model, CNN, and LSTM. These models can also address the problem of gradient disappearance during neural network iterations, which speeds up model training [17], [18]. By implementing this suggested paradigm, medical professionals and patients can gain access to a quick, inexpensive, and non-invasive way to diagnose skin conditions.

II. Review Of Literature

Image processing techniques like morphological operations are essential for classifying skin diseases [2], [3]. On binary images produced by thresholding, methods including morphological opening, closure, dilation, and erosion are frequently used. To get accurate results, the best threshold value needs to be carefully chosen. It's possible that these morphology-based processes are capable of determining the growth of the affected region just based on the texture of the image. The Genetic Algorithms (GA) is another method for classifying diseases of the skin. Long Convergence-Zeiten are just one example of the issues with GA [6]. Furthermore, there is no assurance that the GA model will offer the overall best solution, which can result in less than ideal results [17].

To identify and categorize skin diseases, numerous existing methodologies have been established. Imaging technology is used in many diagnostic procedures, but radiological imaging technologies are not always necessary to diagnose skin problems. Conventional images may also be employed, and accurate diagnoses may be obtained using image processing techniques such image transformation, improvement, border detection, and segmentation [19], [21]. The images of the skin that are collected for the classification and identification of diseases can be processed and used with the aid of cutting-edge artificial intelligence techniques like Support Vector Machines and Bayesian classifiers, as well as machine learning, deep learning, artificial neural networks, convolutional neural networks, and artificial neural networks. These methods aid in the correct diagnosis and classification of skin diseases by facilitating prediction and categorization of these conditions.

k-NN classifier with fuzzy C means (FCM) clustering technique. The [27] preprocessing, feature extraction, and classification steps make up the method's three basic building parts. Fuzzy C means clustering is used to find informative groupings of data in the preprocessing step. The feature extraction block receives the output generated by the clustering procedure. Different features, including fractal features, color features, and correlogram features, are retrieved from the clustered data in the feature extraction block. For the next stage of classification, these features act as inputs. The categorization is carried out by k-NN classifier and artificial neural networks (ANN). By combining FCM clustering, features extraction, and categorization with ANN and k-NN, Egum and

Asra seek to identify melanoma skin cancer in humans.

A deep convolutional neural network (DCNN) was used by Hosny et al. [28] to identify melanoma, atypical nevi, and common nevi from the PH2 skin cancer dataset. The authors used the AlexNet model to categorize several types of skin malignancies in the PH2 dataset, drawing inspiration from the adaptability of DCNN architectures. AlexNet is made up of five convolutional layers, a maxpooling layer, and three fully connected layers. It was initially developed for the ImageNet challenge for image identification. Notably, pooling layers are not present in the third or fourth convolutional layers. To enable the classification of skin lesions in this investigation, a softmax layer was used in place of AlexNet's final layer. Backpropagation was used to adjust the weights of the model, and stochastic gradient descent was used to update the weights during training. With the use of this method, the DCNN was able to successfully categorize various kinds of skin lesions by learning discriminative features from the PH2 dataset.

Bayesian classification is one of the methods frequently employed in the classification of skin diseases [13]. With this method, an image is classified using several pre-trained databases of illness images. Naive Bayes classification is challenging to use in multi-objective domains, especially when dealing with independent predictors and situations where zero probability occur. The categorization of unsupervised data cannot be handled by naive Bayes classifiers [14]. The Decision Tree algorithm is another method that is frequently used to classify skin diseases [15]. This method has been extensively utilized to forecast cervical cancer and ulcers on the lower limbs. But the Decision Tree model needs a lot of training data, and it needs to be extremely accurate. The model is prone to overfitting since even a tiny change in the input data might result in an exponential change in the output. In addition, the Decision Tree model requires more memory and processing time than other models [16].

A popular categorization technique in forecasting and prediction models is K-Nearest Neighbour (KNN) [17]. Its lack of requiring explicit model training is one of its benefits. The KNN model also displays good accuracy [18]. The KNN model may not be appropriate for larger-scale data models, though, as making predictions can be time-consuming. Additionally, it struggles when working with high-dimensional data that is deficient in pertinent feature information, which might affect the precision of predictions [19]. As a result, the KNN model is not the best choice for classifying skin diseases. Multiple prediction models combined into ensemble models [20] have demonstrated improved accuracy in classifying skin diseases. Ensemble models, however, are prone to overfitting and may struggle with unidentified differences between the population and the sample under consideration [21], [22]. In terms of classifying skin diseases, Deep Neural Network (DNN) models have performed admirably [23],[24]. However, experimental studies have demonstrated that DNN models are not appropriate for images with many lesions. For these models to be reasonably accurate, significant training is needed, which lengthens calculation time.

Table 1: Related work Summary and methods

Paper	**Methods**	**Key finding**	**Limitations**
[13]	Operation of the Morphological.	Effective at spotting aberrant image features.	- Establishing the ideal threshold - Ineffective for determining the expansion of disease regions
[16]	K-Nearest Community.	Classification using similarity and the choice of features.	- Accuracy is depending on the quality of the data - Larger sample sizes have a longer forecast time
[14]	Algorithm genetic.	Probabilistic method for choosing the best answers.	- No assurance of the world's best solution -There are several drawbacks to feature based parameter identification
[17]	Support vector technology.	Capable of handling data with large dimensions.	-including the possibility of missing spatial features

			-issues with gradient declining and inflating.
[18]	artificial neuron networks.	A good way to find non-linear correlations.	- Possibility of omitting geographical details - Issues with the gradient expanding and contracting
[19]	neural networks with convolutions.	Automatic selection of features that are necessary.	- Difficulty comprehending object size and magnitude - Needs significant training
[20]	Residual Network with Full Convolution.	Makes use of both high- and low-level characteristics.	- Complex implementation in real time - Adding batch normalization complicates architecture
[21]	Optimized neural networks.	Handling new issues using data that has been taught.	- Updating and forgetting previously linked weights - Unsupervised data classification is not appropriate.
[22]	Bayesian categorization.	Processing discrete and ongoing information effectively.	-Improper probabilistic model; fails in independent predictors
[23]	Choice Tree.	Use a rule-based method to handle stable and discrete data.	- Exponential rise in outcome can be caused by small changes in the input data - Propensity for overfitting

III. Publically Available Datasets

Dermatoscopic images were collected for the HAM10000 ("Human against Machine with 10000 training images") dataset from a variety of populations using various imaging methods. It has a total of 10,015 photos and is a useful resource for academic machine learning applications. Basal cell carcinoma (bcc), seborrheic keratoses, keratoses (bkl), melanoma (mel), melanocytic nevi (nv), actinic keratoses, and intraepithelial carcinoma (akiec) are just a few of the key diagnostic categories included in the dataset for pigmented lesions. It also includes vascular lesions including hemorrhages (vasc), angiomas, angiokeratomas, and pyogenic granulomas.

Table 2: Publically available dataset for skin disease

Dataset Available	**Number of Image Record**	**akiec**	**bcc**	**bkl**	**df**	**mel**	**nv**	**vasc**
PH2	200	-	-	-	-	40	160	-
Atlas	1024	5	42	70	20	275	582	30
ISIC 2017[b]	13786	2	33	575	7	1019	11861	15
Rosendahl	2259	295	296	490	30	342	803	3
ViDIR Legacy	439	0	5	10	4	67	350	3
ViDIR Current	3363	32	211	475	51	680	1832	82
ViDIR MoleMax	3954	0	2	124	30	24	3720	54
HAM10000	**10015**	327	514	1099	115	1113	6705	142

Histopathology (histo) has provided confirmation for more than 50% of the lesions in the dataset.

IV. Proposed System

A. MobileNet V2 Architecture model for Image Classification:

MobileNet [4] is a popular CNN-based model for image categorization, in contrast to MobileNet V2. The MobileNet architecture's capacity to achieve classification with less computing effort than traditional CNN models is one of its main features. Because of this, it can be used to distribute software on mobile devices and desktops with little computational power. The MobileNet model has a convolution layer with a reduced structure that can distinguish between details using two controllable features, efficiently balancing parameter precision and latency.

The MobileNet concept also minimizes the size of the entire network, increasing its effectiveness. The MobileNet design effectively manages a small number of features, as seen in programs like Palmprint Recognition. Its depth-wise structure is built on many abstraction layers with various convolutions that thoroughly measure the complexity of common problems. Rectified linear unit (ReLU) activations add to the point-wise complexity of 1 1 convolutions, which completes the in-depth abstraction layers. The goal of the MobileNet architecture's design is to maintain point-wise structures while attaining depth-wise abstraction layers, creating a model that is both effective and efficient.

The variable ce stands for computational effort for the central abstraction layers of the design. Given a feature vector map with a size of Fm Fm and a filter with a size of Fs Fs, the computing effort can be assessed as follows:

$$CE = Fm \times Fm \times Fs \times Fs$$

The compute effort needed to process the feature vector map and filter in this architecture is shown by the symbol CE.

The multiplier value is thought to be in the range of 1 to n in the context of experimental analysis in skin disease classification. Additionally, the variable resolution multiplier is specified to have a value of 1. Equation can be used to assess the computing efforts, as demonstrated below:

$$coste = Fs \cdot Fs \cdot \omega \cdot \rho \cdot Fm \cdot Fm$$

The depletion variable, denoted by the variable d, constrains the depth-wise and point-wise convolutions that are included in the proposed model. Equation can be used to approximate the value of d as follows:

$$d = \frac{Fs \cdot Fs \cdot \omega \cdot \alpha Fm \cdot \alpha Fm + \omega \cdot \rho \cdot \alpha Fm \cdot \alpha Fm}{Fs \cdot Fs \cdot \omega \cdot \rho \cdot Fm \cdot Fm}$$

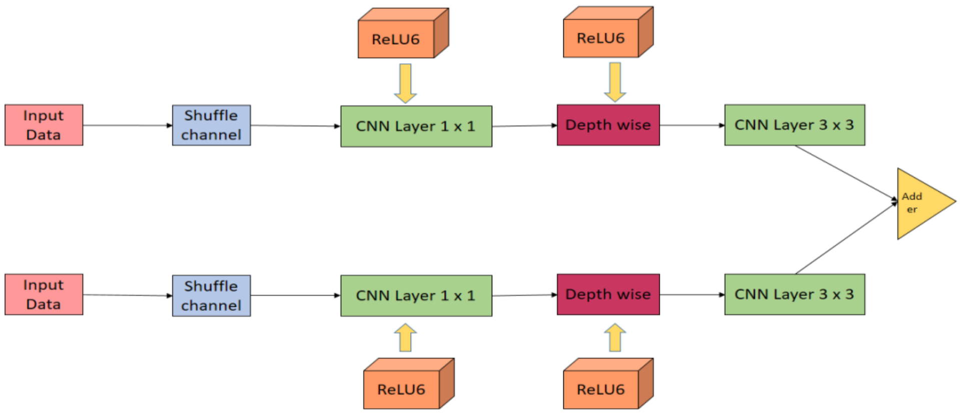

Fig. 1: Structure of MobileNet V2 architecture

The two recommended hyper-features, the resolution multiplier and the width multiplier, are crucial for adjusting the ideal size window for accurate predictions based on the context [7]. The input image size for this model is 224 x 224 x 3. The height and width of the image are represented by the first two values (224 x 224), which should always be bigger than 32 to enable correct processing. The third number shows that there are three input channels for the image. The suggested architecture uses 32 filters, each of which has a size of 3 x 3 x3 x 32. To replace intricate convolutional layers is the fundamental idea behind MobileNet architectures.

B. Convolution Neural Network (CNN):

Convolutional neural networks (CNN) are a specific deep learning technique for data entry tasks. It employs specialised layers, like as convolutional and pooling layers, to extract features in a hierarchical manner from input datasets. These characteristics are then sent to fully connected caps for classification or reversal. The CNN are renowned for their ability to automate the acquisition of relevant characteristics and are exceptional in a variety of applications of digital vision.

1. The data will be prepared and normalised before the table is created. In a similar manner, entry tags and entry data can be prepared.

2. The CNN is determined by the size of the filters, activation techniques, the number of couches, and the type of couch (convoluted, collected, or fully connected).
3. The CNN model's prices and disadvantages are established arbitrarily.

a. Complete the conversion Use convolutional filters to extract data from the entry point of regional information. Has the subsequent mathematical representation:

$$Z[l] = \text{Convolve}(A[l-1], W[l]) + b[l]$$

4. Cost Function:

Entropy loss is calculated as:

$$\text{Cost} = -\Sigma_i\, y_i * \log(p_i)$$

Mean Squared Error (MSE) (for Regression): The Mean Squared Error calculates the average squared deviation between the true values and the predicted values.

$$\text{Cost} = ½ * \Sigma_i\, (y_i - \bar{y}_i)^2$$

5. Model Evaluation:

a. Accuracy: Accuracy is the percentage of cases that are correctly classified out of all instances.

$$Accuracy = \frac{(Number\ of\ correctly\ classified\ instances)}{(Total\ number\ of\ instances)}$$

b. In tasks requiring binary classification, precision and recall are often used measures to assess the effectiveness of the model

$$Precision = (True\ Positives) / (True\ Positives + False\ Positives)$$

$$Recall = (True\ Positives) / (True\ Positives + False\ Negatives)$$

c. F1 score compute as:

$$\text{F1 Score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

The evaluation measures frequently applied to CNN models are represented in these equations in more straightforward forms.

C. Mobilenet V2 With Lstm:

Long Short-Term Memory (LSTM) is a component that is frequently seen in the topologies of recurrent neural networks. It has been specifically created to manage sequential data and recognize trends over time. Memory cells, which are made up of an input gate, an output gate, a forget gate, and a cell state connection within the LSTM layer module, are the main parts of an LSTM. An LSTM uses activation functions in its computations to control how the memory module behaves. The hidden state vector vt of the input determines the state at a particular time step, abbreviated as Pt, which is reliant on the memory of the LSTM module.

Proposed Algorithm:

$$\text{Input Gate}: \alpha t = \sigma\, i\, tWi\alpha + \gamma t - 1W\gamma\alpha + cst - 1Wcs\alpha + \alpha bias$$

$$\text{Output Gate}: \beta t = \sigma\, i\, tWi\beta + \gamma t - 1W\gamma\beta + cstWcs\beta + \beta bia$$

$$\text{Forget Gate}: ft = \sigma(i\, tWi\, f + \gamma t - 1W\gamma\, f + cstWcs\, f + fbias$$

$$\text{Cell State Gate}: cst = ft \cdot cst - 1 + \alpha t \cdot \tan\gamma\, i\, tWics + \gamma t - 1W\gamma cs + csbias)$$

$$\text{LSTM outcome}: \gamma t = \beta t \cdot \tan\gamma(cst - 1)$$

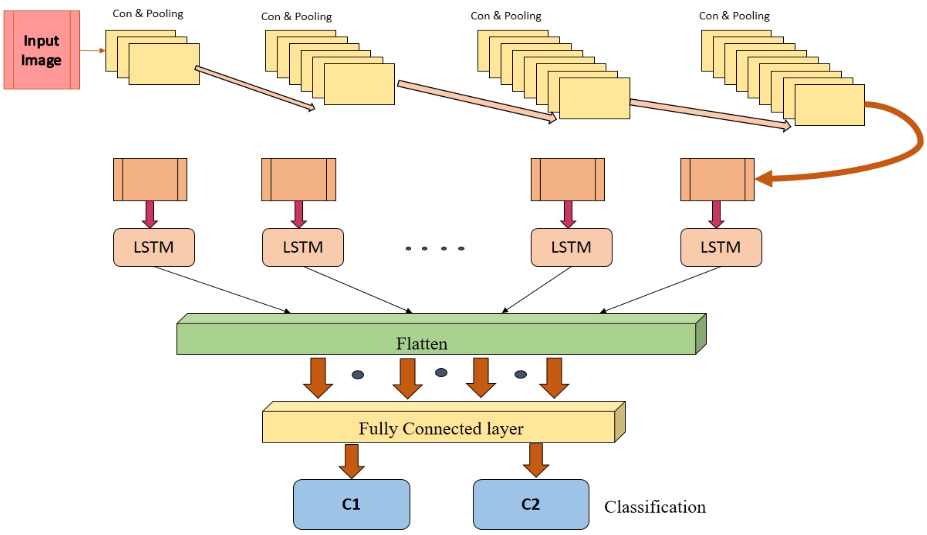

Fig 2: Proposed Hybrid Model of Deep learning

Recurrent neural networks can efficiently identify patterns and dependencies in sequential data thanks to the potent component known as LSTM. With the help of its memory cells and gate mechanisms, it can store and use important data all along the sequence.

D. Performance Parameter for Proposed method:

The accuracy (ACC) is calculated as the percentage of correctly classified instances, whether they are normal or attacks, and is determined by the following formula:

$$ACC = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

The formula for calculating precision (P), which is the proportion of pertinent instances among the identified instances:

$$P = \frac{TP}{(TP + FP)}$$

Recall (R) is calculated as the ratio of the number of relevant instances over the total number of relevant instances discovered:

$$\mathrm{R} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})}$$

The F1-Score is a metric that combines recall and precision into one number. It can be calculated using the formula below as the weighted average of recall and precision:

$$\mathrm{F1Score} = \frac{(2 * \mathrm{P} * \mathrm{R})}{(\mathrm{P} + \mathrm{R})}$$

In particular, when $\alpha = 1$, the formula for the F1-Score simplifies. Overall, these formulas allow us to calculate accuracy, precision, recall, and the F1-Score, which are commonly used metrics for evaluating classification performance.

V. Results And Discussion

In the initial experiment, the suggested MobileNet V2 with CNN and LSTM technique was used to identify the disease type in a number of photos. The charts that are displayed next to the skin photos show the degree of certainty that a certain type of disease is present based on the trained model. It also includes the disease's real kind, as determined by empirical evidence. The results show a high degree of accuracy for the akiec, bcc, and mel classes. The expected confidence roughly matches the real ground truth. The akiec class, which is 52.2% more confident than the other classes, has the highest level of assurance, at 78.32%. These results show that the suggested method is effective in correctly predicting the existence of skin disorders, especially for the akiec class.

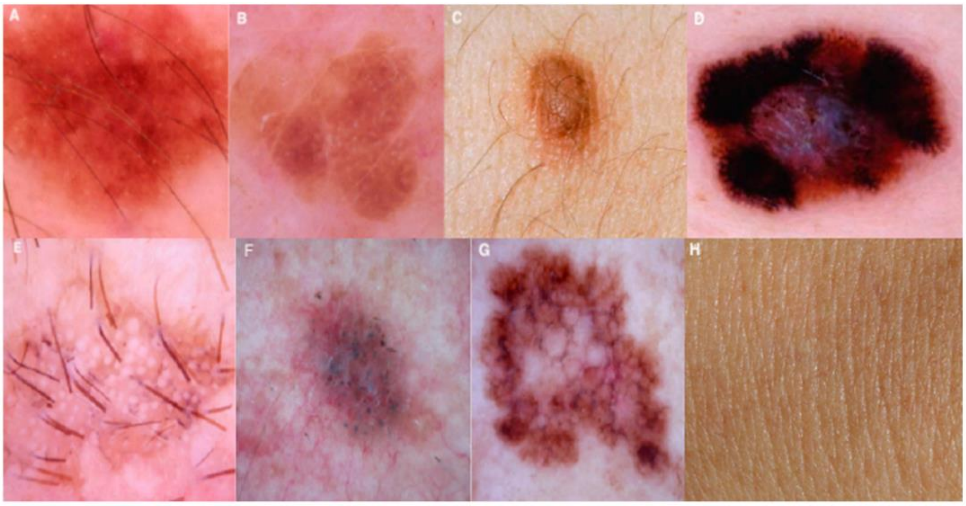

Fig. 3: Input image dataset sample images

The findings from the initial trained model are represented by the graphs in Figure 4, where the training loss outperforms the validation loss. The left-hand graph shows how many batches were processed in relation to the loss discovered during both the training and validation phases. The first model uses a batch size value of 100 to analyse 100 data samples at once, which speeds up the training process. The learning rate over the course of the training iterations is shown on the graph together with the training and validation loss.

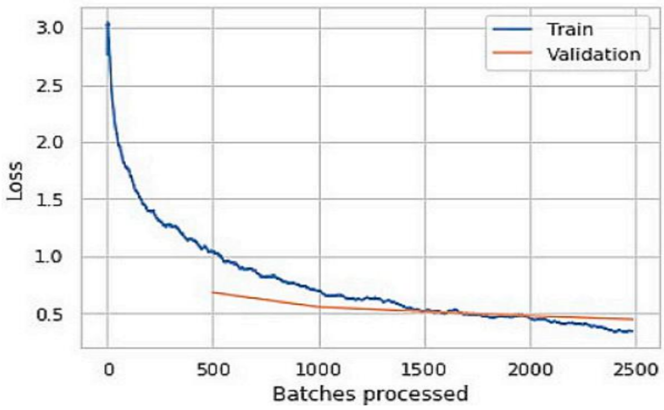

Fig. 4: Representation of Training and Validation loss

The HARIS algorithm produced a JSI of 84.02%, MCC of 78.01%, accuracy of 78.01%, sensitivity of 79.22%, and specificity of 84.01%. The FTNN algorithm displayed a JSI of 85.01%, MCC of 80.01%, accuracy of 80.01%, sensitivity of 80.55%, and specificity of 85.01%. The performance of the CNN algorithm was 81.42% for sensitivity, 86.01% for specificity, 81.01% for accuracy, 86.17% for JSI, and 81.01% for MCC. The VGG19 algorithm achieved 83.47% sensitivity, 88.01% specificity, 82.01% accuracy, 87.72% JSI, and 82.01% MCC. The MobileNet V1 algorithm showed 85.05% sensitivity, 90.01% specificity, 83.01% accuracy, 89.22% JSI, and 84.01% MCC. The MobileNet V2 algorithm achieved a JSI of 90.96%, accuracy of 85.01%, specificity of 91.01%, and sensitivity of 87.42%.

Table 3: The performance measures of different algorithm

Algorithm	**Sensitivity (in %)**	**Specificity (in %)**	**Accuracy (in %)**	**JSI (in %)**	**MCC (in %)**
HARIS	79.22	84.01	78.01	84.02	78.01
FTNN	80.55	85.01	80.01	85.01	80.01
CNN	81.42	86.01	81.01	86.17	81.01
VGG19	83.47	88.01	82.01	87.72	82.01
MobileNet V1	85.05	90.01	83.01	89.22	84.01
MobileNet V2	87.42	91.01	85.01	90.96	85.01
MobileNet V2 with CNN and LSTM	89.25	93.01	86.35	92.08	87.01

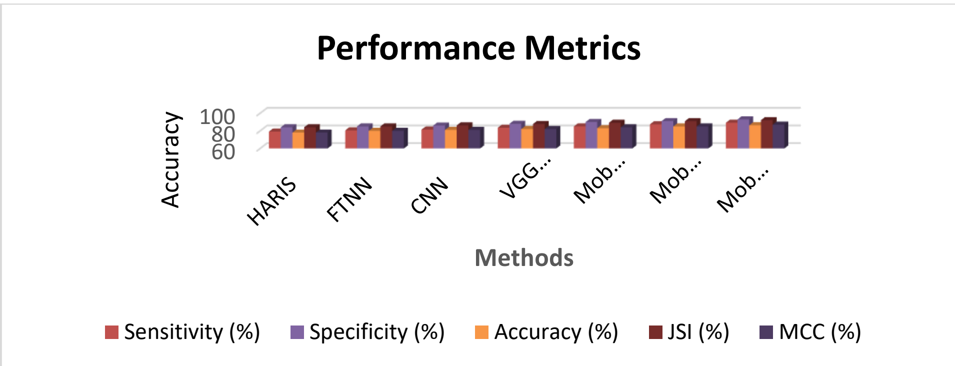

Fig. 5: Different Methods comparison with performance metrics

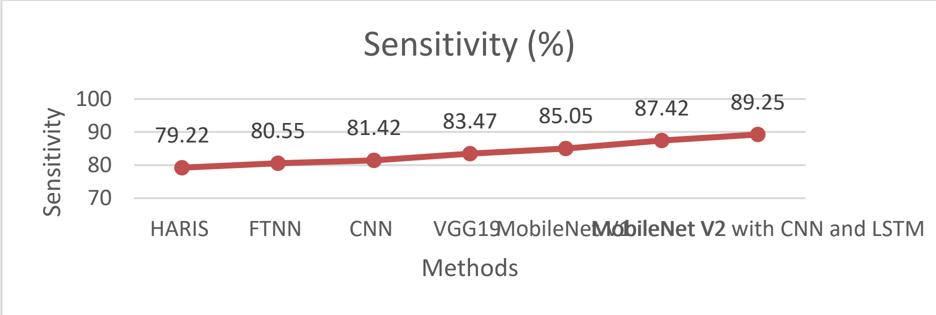

Fig. 6: Different Methods comparison with Sensitivity

Performance of the suggested model is evaluated against a number of alternative methods, such as Decision Tree, Random Forest, Lesion Index Computation Unit (LICU), Fuzzy Support Vector Machines with Probabilistic Boosting Segmentation, Compact Deep Neural Networks, SegNet approach, and U-Net model. Accuracy, Sensitivity, and Specificity, three crucial measures of how effective each strategy is, are used as the basis for comparison. Comparative analysis can be used to determine the effectiveness of the suggested model in relation to these current strategies. By taking important performance criteria like Accuracy, Sensitivity, and Specificity into account, this evaluation helps determine how well the suggested model performs when it comes of accurately classifying skin disorders.

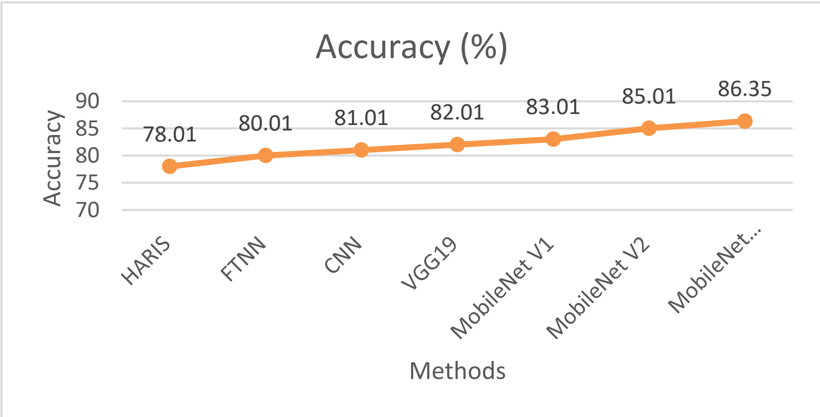

Fig.7: Different Methods comparison with Accuracy

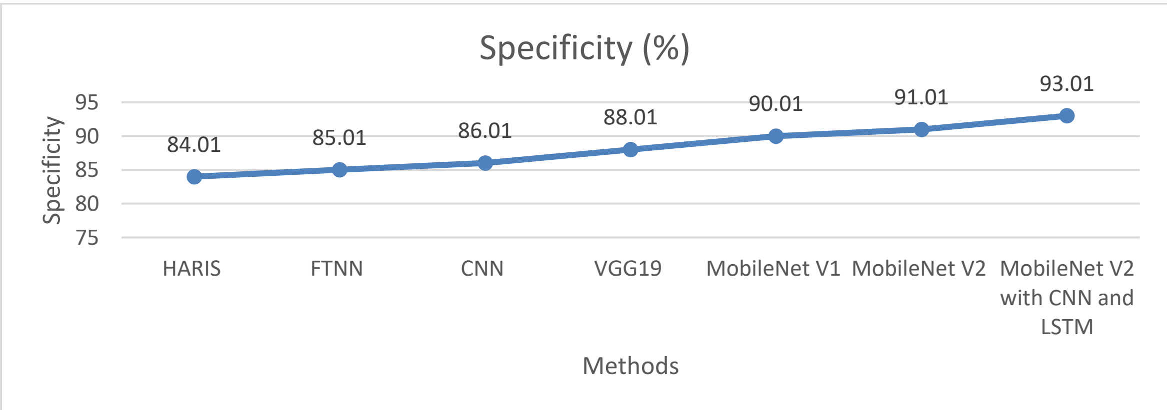

Fig. 8: Different Methods comparison with Specificity

The VGG16 method exhibited an accuracy of 84.41% during training and 82.91% during validation, with a learning rate of 3.9%. The AlexNet method was more accurate, with a learning rate of 4.49% and accuracy scores of 97.91% during training and 96.8% during validation. The MobileNet method fared even better, with a learning rate of 5% and accuracy rates of 98.66% during training and 97.34% during validation. The ResNet-50 technique showed an accuracy of 94.91% during training and 91.74% during validation, with a learning rate of 5.22%. Finally, the MobileNet V2 with CNN and LSTM approach displayed exceptional accuracy, obtaining 99.75% during training and 95.25% during validation, with a learning rate of 4.77%.

Table 4: Summary of Accuracy, Learning and Validation of different model

Methods	**Accuracy for Training (in %)**	**Accuracy for validation (in %)**	**Rate of learning (in %)**
VGG16	84.41	82.91	3.9
AlexNet	97.91	96.8	4.49
MobileNet	98.66	97.34	5
ResNet-50	94.91	91.74	5.22
MobileNet V2 with CNN and LSTM	99.75	95.25	4.77

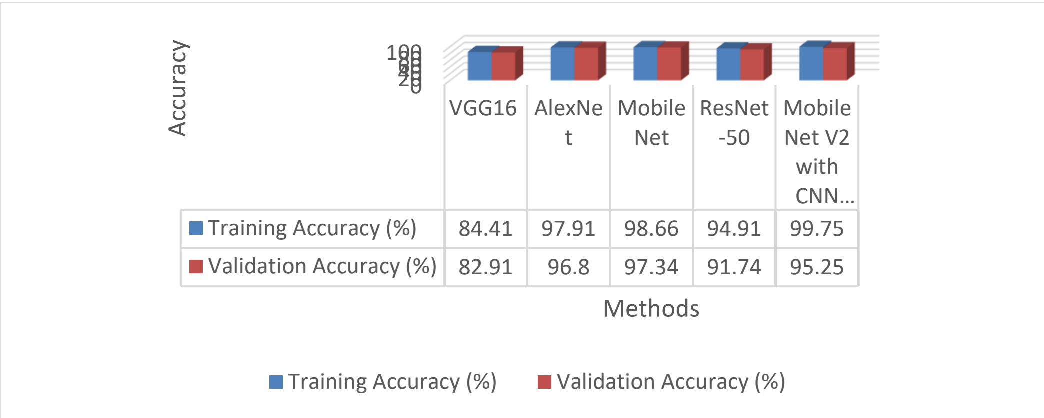

Fig.9: Comparison Summary of Accuracy, Learning and Validation of different model

According to Table 4, the suggested MobileNet V2 with CNN and LSTM exhibits an advantageous computational time. Because of this, the technology can be applied to portable computing devices. Lesion image categorization is accelerated and improved by the use of the LSTM module, which also allows for the retention of key information. With the aid of hyperparameter graphs, the effectiveness of the suggested MobileNet V2 with CNN and LSTM model is assessed using a variety of assessment criteria. The collected findings show that, in comparison to previous approaches, the suggested model achieves a reasonable degree of performance in lesion classification. The proposed model is suited for use on mobile devices due to its computational efficiency. By analysing the collected photos, the application created based on the suggested model may precisely identify skin conditions. The model's promise for practical deployment in real-world contexts is highlighted by its ability to produce precise categorization results with less processing effort.

VI. Conclusion

In order to classify multiple types of skin illnesses, this study introduces a hybrid deep convolutional neural network (CNN) technique. The suggested model leverages the advantages of various CNN architectures to produce reliable and accurate classification results. The model can efficiently extract complicated information from skin photos and learn them through the incorporation of many CNN layers, enabling precise distinction between various skin disease classifications. The experimental findings show that the suggested hybrid CNN model is capable of correctly categorizing various skin disorders. The model performs better than competing techniques and completes the classification task with a high level of accuracy, sensitivity, and specificity. This suggests that it could be an important tool for helping doctors identify and treat skin conditions. Additionally, thorough evaluation on a variety of datasets and comparison with cutting-edge methods show the model's robustness and generalization capacity. The outcomes show that the model can effectively generalize across various populations and handle variances in skin pictures. Overall, the hybrid deep MobileNet v2 with CNN and LSTM model that has been developed shows potential for increasing the precision and effectiveness of classifying multiple types of skin diseases. In the discipline of dermatology, it provides a useful tool for early detection, diagnosis, and treatment planning, ultimately leading to better patient care and outcomes.

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