A review on Skin Cancer Detection Using Combined Decision of Deep Learners

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ABSTRACT

Cancer is a fatal illness that develops when body cells grow out of control. Cancer has been dubbed the most significant public health issue due to the high number of deaths it causes each year. Any area of the human body, which may be made up of trillions of cells, might develop cancer. Skin cancer, which arises in the epidermis, is one of the most common types of cancer. In the past, protein sequences and several imaging modalities have been utilised to diagnose skin cancer using machine learning approaches. The disadvantage of machine learning techniques is that they necessitate human-engineered features, which is a very time-consuming and difficult process. By offering the capability of automatic feature extraction, deep learning partially resolved this problem. This study uses the ISIC public dataset to detect skin cancer using convolution-based deep neural networks. Cancer detection is a delicate matter that is prone to mistakes if it is not promptly and precisely identified. Each machine learning model's ability to identify cancer is constrained. It is anticipated that the decision made by the group of learners will be more accurate than that of the individual learners. To make a better choice, the ensemble learning technique takes advantage of the diversity of learners. Therefore, by combining each learner's decision for delicate topics like cancer diagnosis, the prediction accuracy can be improved.

This article develops an ensemble of deep learners for skin cancer detection employing learners from VGG, Caps Net, and Res Net. The findings demonstrate that, in terms of sensitivity, accuracy, specificity, F-score, and precision, the combined judgement of deep learners is better than the finding of individual learners. The study's experimental findings offer strong justification for its application in the identification of various diseases.

INDEX TERMS: convolutional neural network, skin lesion, ensemble learning, deep learning, combined decision, skin cancer

I. INTRODUCTION

The human body's cells normally go through a predictable life cycle. For the body to work correctly, its creation, functional time, and death should occur in that order.

Cancer is one of the many diseases that arise when the order is upset. Anywhere in the human body, which may be made up of billions of cells, cancer can develop. Certain body cells in cancer begin to divide without being stopped, and these cells spread to the surrounding tissues. In humans, cells typically proliferate and divide to create new cells in response to bodily needs. Cells develop, age, or get depleted during the process; as a result, the cell dies and is replaced by new, fresh cells. Once cancer starts, the methodical, exact process of breaking cells is destroyed.

Consequently, there is a significant development in the threshold of cell injury and abnormalities. New cells are only created when they are needed, and cell survival only occurs when the old cells die. If the cells are not needed, they will continue to divide and could lead to the development of a tumour [1].
Cancer can cause both benign and malignant tumours. The majority of tumours made up of cancerous cells are malignant. When a tumour spreads or attacks nearby tissues, it is said to be malignant. Malignant tumours break,

and some of the malignant cells travel to other regions of the body via the blood or lymphatic system, creating secondary tumours that are far from the original tumour. A benign tumours, in contrast to malignant tumours, do not split within the body or engulf tissues. Benign tumours are typically larger. However, benign tumours cannot regrow after removal, although malignant tumours may occasionally do so following surgery. A benign tumour in the brain poses a serious risk to life, but many benign tumours in other parts of the body are often not harmful [2]. Figures 1 and 2 display the dermoscopy picture samples for benign and malignant conditions, respectively.

The human body can be shielded by the skin from heat, sunlight, injuries, and bacterial or viral diseases. In addition to storing water and fat, the skin aids in regulating body temperature. Skin cancer is the most prevalent type of cancer and the biggest public health concern.
Although skin cancer can begin anywhere on the body, it usually begins where the skin is exposed to sunlight. Different layers of skin are present. However, skin cancer typically starts in the epidermis layer, which is the outermost layer.
Squamous cells and basal cells are two of the many types of skin cancer. Non-melanoma skin cancers are a type of skin cancer.

Treatment for non-melanoma skin cancer is effective, and it seldom spreads to other parts of the body. Among the various types of skin cancer, melanoma is the most dangerous. Malignant skin lesions can be classified as either melanocytic (like melanoma) or non-melanocytic (like basal cell carcinoma). Melanoma is the most severe, aggressive, and uncommon type of skin cancer [2].
Melanoma skin cancer will most likely infect nearby tissues and spread to other parts of the body if it is not detected in a timely manner. Every year, there is an increase in the number of melanoma cases. A reputable cancer organisation called the Melanoma Foundation [3] projected that melanoma will kill 9730 people in the US.

It also calculated that since 1973, the number of documented cases has increased by 200% to 87,110. The literature has developed machine learning and deep learning-based methods for detecting cancer using protein sequences and image data. Human-engineered characteristics are necessary for machine learning techniques. Manual feature extraction is a laborious and time-consuming process that relies on the subjectivity of specialists. Deep learning techniques have partially overcome this issue. Automatic feature engineering is carried out by deep learning techniques.

Due to this property, in current years, deep convolutional neural networks (DCNN) gained popularity and researchers have been using DCNN to solve problems in all domains including medical image classification. On the other hand, ensemble learning methods have recently been presented as a way to improve classification performance [14], [15], [16]. Unfortunately, due to the unavailability of huge amounts of medical data, the performance of deep learning models is very limited. As there aren’t enough labelled medical images that’s why researchers commonly use transfer learning approaches. The goal of transfer learning is to apply the information acquired from solving one problem to another that is related. Additionally, each learner's performance is restricted to making decisions on delicate matters like cancer detection.
Individual learners' decisions can be combined to solve this problem. It is anticipated that the decision made by the group will be more correct than that of the individual students. Combining the decisions of discrete learners can improve the accuracy of skin cancer detection. An ensemble of deep learners using VGGNet, CapsNet, and ResNet has been built in the presented work. The outcomes show that the suggested ensemble model outperformed the individual deep learners.

The remainder of the paper is organised as follows: section II presents related work; section III describes the suggested technique; section IV presents results and discussion; and section V reviews the conclusion and future work.

II. RELATED WORK

A great deal of work has been done utilising deep learning and machine learning techniques for the identification of skin cancer. By extracting the manual features from dermoscopy images, machine learning techniques detect skin lesions. In [4], Waheed et al. developed a machine learning method for identifying melanoma in dermoscopic pictures. Mohsin et al. used discriminating information from mutant genes in protein amino acid sequences to diagnose cancer [5].

In [6], Abdul M. et al. created a cancer prediction method utilising support vector machines and nearest neighbours. A support vector machine has been used in [7] to diagnose melanoma. They employed segmented pictures for cancer classification. These machine learning techniques are restricted to dermatologists' knowledge and require customised features. However, DL models have demonstrated significant performance for a variety of medical image classification applications and offer automatic feature extraction. Alizadehet al. [34]

developed a novel method for the automatic identification of skin cancer using a deep learning technique. By combining two CNN models with additional classifiers and extracting texture features from images, they use an ensemble technique to identify cancer. The system was then assessed using several assessment metrics on the PH2, ISIC 2016, and ISIC 2019 datasets.

FIGURE 1. The skin lesion diagnosis of malignant.

FIGURE 2. The dermoscopic image sample of benign.

To distinguish between 11 distinct kinds of skin conditions, Jaing et al. [35] introduced a novel deep-learning bases model known as residual attention network that have been trained on 1167 datasets of histological images collected over a ten-year period. They use reinforce feature learning to identify a region of interest in an image, followed by a class activation map to obtain a graphic representation of their suggested network. Zhang [36] suggested a deep learning algorithm for melanoma detection.
The ISIC 2020 dataset was used to train the CNN model Ef centNet-B6.
They claimed to have used this model for the first time to identify skin cancer using transfer learning, and they evaluated their system using metrics based on the area under the receiver operating characteristic curve. Yuan et al. used deep CNN to segment skin lesions [8].

Yu et al. automatically identified melanoma in dermoscopy images using very deep residual networks [9]. Bi et al. segmented dermoscopic images using multi-stage fully convolutional neural networks [10]. In [11], Ulzii-Orshikh Dorj et al. used a convolutional neural network to classify skin cancer. Esteva et al. used deep learning to classify skin cancer at the dermatologist level [12]. A combination of deep neural networks was used by Mahbood et al. to classify skin lesions [13].

These days, researchers frequently employ ensemble networks to enhance classification performance. The findings are often obtained by combining predictions from multiple models using majority voting and stacking approaches after each model has been trained separately. An ensemble network was proposed by Aboulmira et al. [33] for the classification of skin lesions. To improve the classification rate, the several models are integrated after the features are extracted using the individual models (118200).
The ISIC-2018 publicly accessible dataset was used to evaluate the suggested ensemble of seven predictors, and it performed better than previous approaches.

Early skin cancer detection has been carried out employing Fix Caps is an enhanced capsule network (Caps Net) in [32]. The suggested approach produced a broader receptive field.
in contrast to the baseline.

In addition to improving detection performance, Caps Net's huge kernel size of 31*31 lowers computational overhead. By maintaining both the short-term and long-term correlations, Cao et al. [31] proposed a unique inter-pixel correlation learning (ICL) network for early-stage skin lesion diagnosis. The suggested approach is based on the encoder-decoder architecture, where global information is recorded using pyramid transformer

inter-pixel correlations (PTIC) and local semantic correlations are reinforced using local neighbourhood metric learning (LNML).

Using public challenge datasets, this two-stage framework improves segmentation performance by increasing intra-class consistency and inter-class variance.
Using dermoscopic pictures, Javaid et al. [45] presented machine learning-based skin cancer segmentation and classification. The OTSU thresholding method was used to segment the picture, and different features, such as the grey level co-occurrence matrix (GLCM), the histogram of orientated gradient (HoG), and colour features, were retrieved for ML model classification. Skin pictures have been used in another machine learning-based method to diagnose skin cancer [46]. First, the median filter is utilised to identify the skin. Next, the mean shift segmentation is employed for segmentation.

A deep learning-based approach that classifies skin cancer using the deep learning model U-net was proposed by Araújo et al. [37]. Together with U-net, they create a system for automatically segmenting skin cancer photos, which is then integrated with various post-processing methods to enhance and restore the images. Their network is trained using the PH2 and DermIS datasets, and it is then validated on sensitivity, precision, accuracy, AUC, Dice, and Jaccard.
A CNN was used by Subramanian et al. [38] to categorise and identify various forms of skin cancer. Raja makes use of HAM10000 (Human against Machine with 10000 training images), which includes 10015 photos of skin cancer.

They then use accuracy, precision, recall, and F score to compare their system with other cutting-edge models in order to validate their model. A deep convolutional neural network model was presented by Ali et al. [43] for the classification of skin cancer.
To improve outcomes, they preprocess the dataset to eliminate noise before applying the model. After training their model on the HAM1000 dataset, they compare it to various deep learning-based models such as Alex Net, Res Net, VGG-16, Dense Net, Mobile Net, etc. Hemsi et al. [47] used deep neural networks to accurately detect skin cancer. Seven moles of skin cancer are classified using both the plain and hierarchal classifiers developed using the suggested framework assessed on the HM10000 dataset.

In [48], an enhanced VGG model for the diagnosis of skin cancer was mentioned. Batch normalisation and a fully connected network have been added to the baseline VGG model to enhance its diagnostic performance. In [17], Bajwa et al. proposed an ensemble model to classify seven different types of skin cancer using the ISIC dataset and various optimised models such as ResNet-152 [18], SE-ResNeXt101 [19], DenseNet-161 [18], and NASNet [19]. By pooling the judgements of numerous independent learners, the ensemble machine learning technique improves classification accuracy [20]. The ensemble model is expected to increase classification accuracy by utilising the diversity of individual models to provide a combined judgement [21], [22].
Pacheco et al. [39] used various deep learning models and the information fusion technique to combine metadata with the photos in order to classify skin cancer.Efficient Net, DenseNet-121, MobileNet-v2, ResNet-50, and VGG-13 were trained using two distinct datasets, ISIC 2019 and PAD-UEFS-20, as well as the patient's various clinical characteristics, including age, gender, anatomical area, cancer history, and skin prototype. Using the HAM10000 dataset, which includes 10015 dermoscopic skin cancer images, Jusman et al. [40] trained two deep learning models, VGG-16 and Multi-layer Perceptron, for the classification of skin cancer.

Dermoscopic pictures of skin cancer. Based on accuracy and model time, they evaluate the two models and conclude that VGG-16 outperforms the multilayer perceptron. Togacar et al. [41] introduced a novel model to identify skin cancer by restructuring the dataset for training with an autoencoder model and utilising the deep learning convolutional model MobileNetV2 in conjunction with the spiking network to yield the best results. They make use of the ISIC skin cancer dataset, which includes 1800 benign and 1497 malignant tumour images. In order to provide a fully automated method for segmenting cutaneous melanoma at its earliest stage, Nawaz et al. [42] suggested a deep learning-based approach that included fuzzy k-means clustering and faster region-based convolutional neural networks (RCNN). The dataset is pre-processed to eliminate noise and other illumination issues before the model is used. The model is trained and assessed using the ISBI-2016, ISIC-2017, and PH2 datasets. Skin cancer has been classified into two classes (benign and malignant) in [9], [23], [24], and [25].

separate learners' performance is limited to making decisions, which can be addressed by combining their separate decisions. It is anticipated that the combined choice will be more accurate than the individual learners. Combining discrete learners' decisions can increase the accuracy of skin cancer detection. VGG Net, Caps Net,

and Res Net were used in this study to build an ensemble of deep learners, and the findings show that the suggested ensemble performed better than the individual learners.

III. PROPOSED METHODOLOGY

There are two phases to the development of the suggested deep learning-based ensemble technique. Using benign and malignant images from the International Skin Imaging Collaboration (ISIC) skin cancer images repository, three deep learning models of VGG, CapsNet, and ResNet were developed in the first step. The results of deep learners were merged in the second step using majority weighting. Fig. 3 displays the block diagram of the suggested method for detecting skin lesions.

A. DATASET

The International Skin Imaging Collaboration (ISIC) pictures repository is the source of the dataset, which includes both malignant and non-cancerous photos [26]. ISIC is a collaboration between academics and business to support the development of digital skin imaging applications that will shorten the melanoma life cycle. ISIC is creating guidelines to deal with the terms, tools, and methods used in skin imaging, paying particular attention to important concerns like privacy and interoperability. There are 25,000 photos in the ISIC 2019 repository. A variety of malignant and non-cancerous picture types make up the dataset. Binary class classification has been carried out utilising 2800 benign and 3000 malignant images in the suggested ensemble approach. Because there are only 2800 benign photos in this dataset, the number of malignant images is equal to the number of benign images in order to prevent algorithmic bias. Eighty percent of the total photos in the collection are used as training data.

The test data was derived from the remaining photos. The photos in the dataset come in a variety of sizes.

In the suggested method, images have been downsized to 224 x 224 x 3

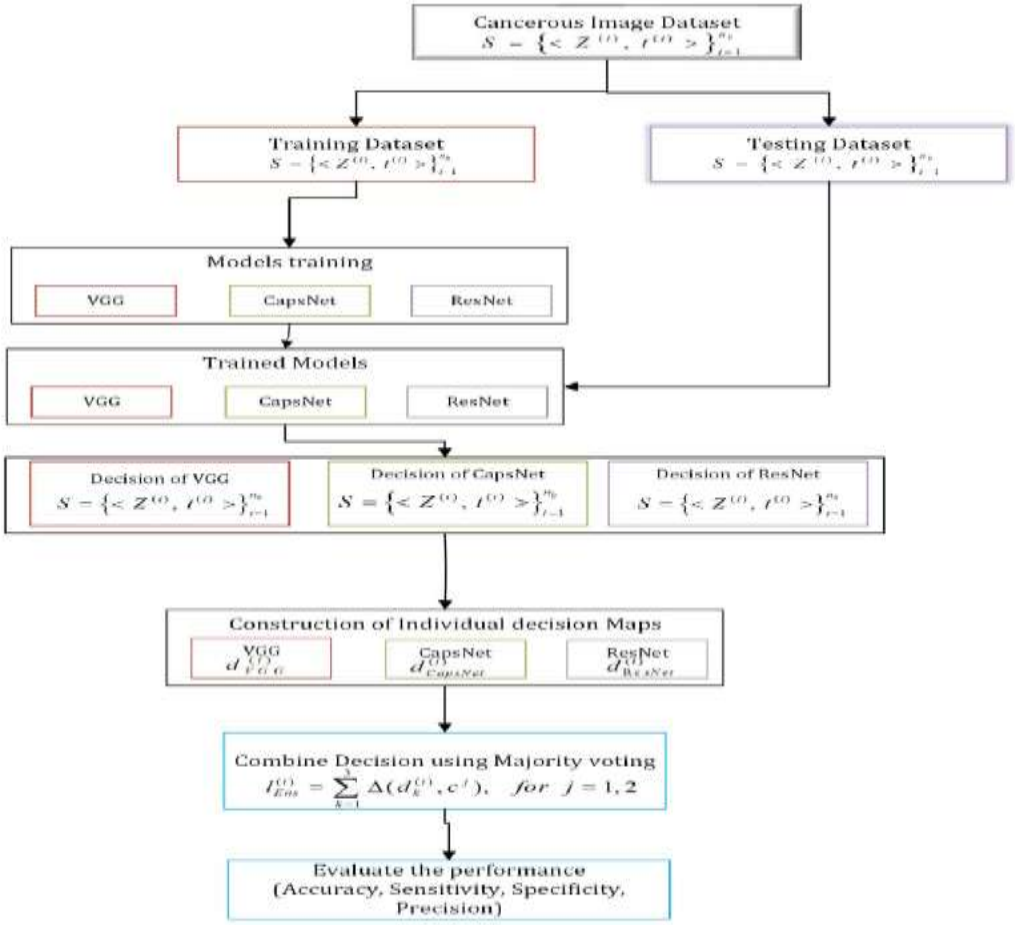

FIGURE 3. Block Diagram of proposed system.

B. NEURAL DEEP NETWORK

Three distinct convolution-based deep neural network models-VGG, Caps Net, and Res Net-have been created in order to create the suggested ensemble.

C. DIFFERENT MEASURES USED TO EVALUATE PERFORMANCE

The following quality metrics were applied to evaluate the suggested performance of techniques:

1) ACCURACY

Accuracy is a measure of the classifier's capacity to correctly predict the class labels.It is computed as follows:

$$\text{Accuracy} = \frac{TN + TP}{FN + FP + TN + TP} \qquad (14)$$

2) SENSITIVITY

The most often used parameters in epidemiological and medical research are sensitivity and specificity, however the majority of statisticians in mathematical fields are ignorant of them. It evaluates the classifier's capacity to accurately predict the positive class. This is how the sensitivity value is determined.

$$\text{Sensitivity} = \frac{TP}{FN + TP}$$

3)SPECIFICITY

Specificity measures the classifier's capacity to accurately forecast the negative class. The definition of "specificity" is as follows:

$$\text{Specificity} = \frac{TN}{FP + TN}$$

4) F-SCORE

The statistical tests are measured using the F-score. Recall and Precision are used by F-score to calculate prediction accuracy. The weighted average of recall and precision can also be used to measure the F-score. The number of right guesses divided by the total number of predictions is how the recall is calculated. Precision is de ned as the number of accurately predicted predictions divided by the number of predictions returned. The value of the F-score is calculated by:

$$F - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (17)$$

where, Precision $= \frac{TP}{TP+FP}$ While Recall $= \frac{TP}{TP+FN}$

5) CONFUSION MATRIX

A confusion matrix represents the righteousness and false hood of the machine learning approach. The size of the con fusion matrix is directly proportional to the number of things to be predicted. The rows of the confusion matrix show the prediction of the machine learning algorithm on the other side columns of the confusion matrix represent the actual value of known truth. Then the top left corners as shown in Fig. 8 contain a true positive, and a true negative is at the bottom right-hand corner. While the left-hand bottom corner of Fig. 8 contains a

False Negative, the top right-hand corner contains the False Positive.

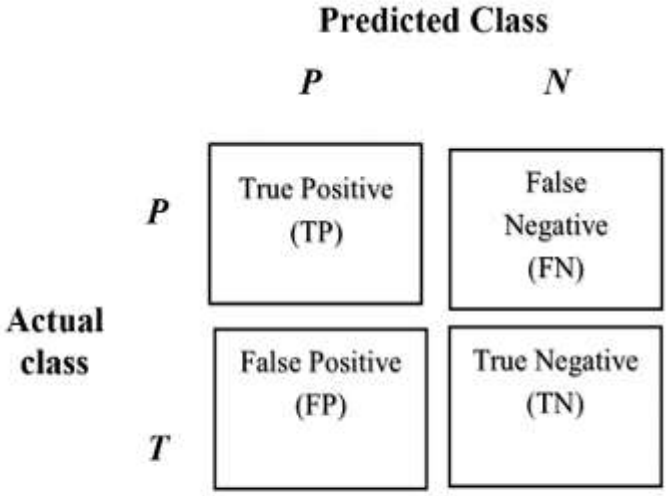

FIGURE 8. Confusion matrix.

IV. RESULTS AND DISCUSSION

The performance analysis of the suggested model, which includes both individual deep learners and deep learners-based ensemble systems created in [27], is expressed in Table 1. Additionally, the results of the suggested method are contrasted with the various machine learning techniques developed in [7]. Table 1 shows that VGG, CapsNet, and ResNet offer accuracy values of 79%, 75%, and 69%, respectively. The prediction accuracy of the previously presented ensemble model is 93.5%. Additionally, Table 1 demonstrates that VGG, CapsNet, and ResNet have sensitivity values of 66%, 72%, and 75%, respectively. Additionally, the sensitivity value of the suggested ensemble model is 87.25%.

Compared to individual learners, the suggested ensemble model classifies the malignant photos even more accurately by taking into account the specified values. However, it is found that the specificity values of VGG, CapsNet, and ResNet are 93%, 77%, and 63%, respectively. The ensemble system that has been suggested has a lower specificity value of 84%, which indicates that the suggested model has detected cancer more accurately by combining the decisions of individual learners and taking advantage of their diversity. In contrast to individual learners, the suggested ensemble model has a higher F-Score, lower False-positive, and greater precision values of 92%, 16%, and 94%, respectively, according to the table. In addition, Table 1 shows how well the suggested method performs in comparison to the deep learning-based ensemble system created in [15]. The table indicates that in terms of accuracy, sensitivity, and specificity, the suggested ensemble outperforms the ensemble approach developed in [27].

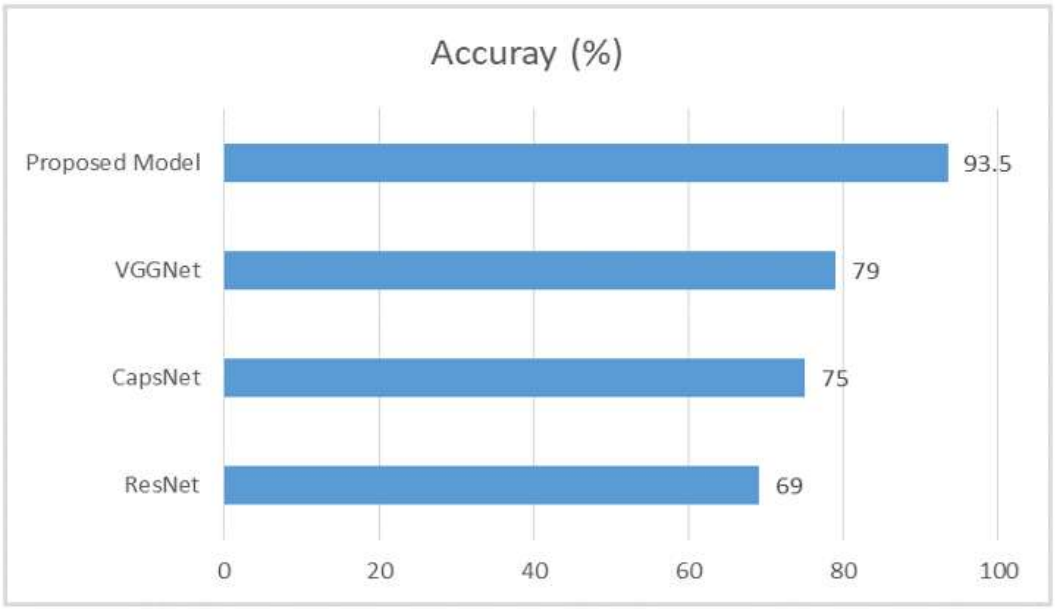

FIGURE 9. The accuracy comparison of the proposed model and individual learners.

However, Table 2 presents the information regarding the performance comparison between the different machine learning techniques created using the ISIC dataset in [7] and the suggested deep learning ensemble. The segmented image is used by the authors in [7] to diagnose cancer.

Following that, Table 2 shows that in terms of accuracy, precision, recall, and F-Score, the suggested ensemble outperforms the individual machine learning model of support vector machine (SVM), K-nearest neighbour (KNN), Naïve Bays (NB), and random forest-based ensemble approach. This table demonstrates that the SVM outperforms the suggested ensemble model in terms of accuracy. One of the reasons for this is because segmented images are used in the development of the SVM.
The performance of several deep learning models is compared with the suggested model in Table 3. Fig. 9 shows that the suggested model has performed better than cutting-edge techniques in a number of performance criteria, including accuracy, sensitivity, specificity, etc.
The test and training accuracy of each student is displayed in Figs. 10 to 12. Fig. 10 displays the VGG model's accuracy. The figure shows that VGG's test accuracy is 79% and its training accuracy is up to 0.80.
Fig. 11 displays the CapsNet model's accuracy. The figure shows that the CapsNet model's test accuracy is 73% and its training accuracy is 75%.

TABLE 1. Comparison of Performance between presented ensemble approach and the individual Learners.

Models	Accuracy	Sensitivity	Specificity	F-Score	False-positive	Precision
VGG	79	0.66	0.93	0.78	0.07	0.91
CapsNet	75	0.72	0.77	0.74	0.23	0.76
ResNet	69	0.75	0.63	0.68	0.37	0.67
Deep Learning Ensemble in [27]	73	0.82	0.62	-	-	-
Proposed Ensemble	93.5	0.87	0.84	0.92	0.06	0.94

TABLE 2. Comparison of performance between presented approach and various machine learning models.

Model	Accuracy	Precision	Recall	F-Score
RF	82.22	42.37	48.26	45.12
SVM	85.19	42.59	50.15	46.05
KNN	79.26	45.04	47.55	45.92
Naïne Bayes	45.62	43.86	44.4	45.25
Proposed Ensemble	93.50	94.0	87.0	92.0

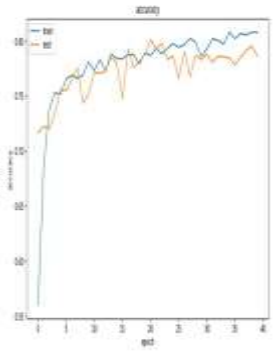

FIGURE 10. Accuracy of VGG16.

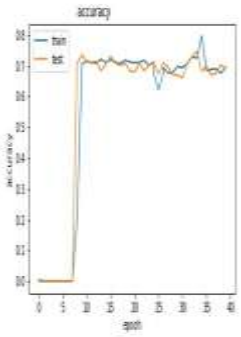

FIGURE 11. Accuracy of CapsNet.

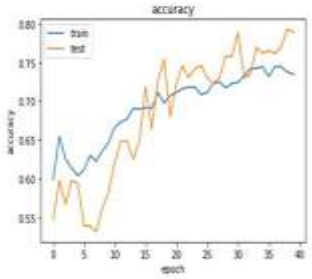

FIGURE 12. Accuracy of ResNet.

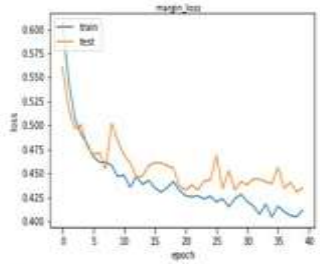

FIGURE 13. Loss of VGG16.

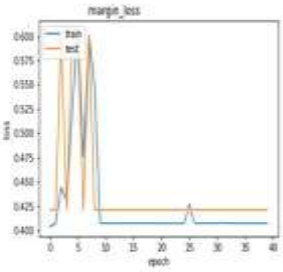

FIGURE 14. Loss of CapsNet.

The ResNet model has an 80% training accuracy, as seen in Fig. 12. Figures 13 through 15 display each learner's training and exam loss. The training losses for VGG, CapsNet, and ResNet are 0.40, 0.41, and 0.35, respectively. A machine learning algorithm's righteousness and falsity are represented by a confusion matrix. Fig. 16 displays the VGG confusion matrix. The figure shows that the VGG model has greater classification mistakes in the class that is not malignant. Fig. 17 displays the CapsNet confusion matrix. In the non-cancerous class, the CapsNet model is found to have greater classification mistakes. The ResNet confusion matrix is displayed in Fig.18.The confusion matrix indicates that the ResNet has higher misclassifications in the Cancerous class. The confusion matrix of the suggested ensemble model is displayed in Fig. 19. The suggested ensemble model has greater classification errors in the non-cancerous class, as can be observed from the confusion matrix. The confusion matrix indicates that, in comparison to individual models, the suggested model has lower classification errors for both malignant and non-cancerous classes.

A. ABLATION RESEARCH

The performance study of the suggested ensemble network of VGG16, ResNet, and CapsNet is shown in this section. The ISIC public dataset for skin cancer classification from dermoscopic pictures is used to assess the model's performance.

The ideal hyperparameters for the suggested model are chosen, including 40 epochs, a learning rate of 0.001 with a batch size of 32, and a stochastic gradient descent (SGD) optimiser. The training assessment is carried out using various batch sizes. The accuracy of the suggested ensemble network in comparison to individual learners is displayed in Fig. 9. It is clear from Fig. 9 that the suggested model had the highest accuracy of 93.5%. The accuracy curve for each learners' training and testing accuracy is displayed in Figures 10 through 12. The validation loss evaluation of VGG16, CapsNet, and ResNet is displayed in Figures 13 through 15. For the suggested ensemble, the optimal loss function of 0.06 was likewise attained. VGGNet, CapsNet, ResNet, and the suggested approach have classification training times of 106, 136, and 188 seconds, respectively.The suggested model is more weighted because to the greater performance gap, and there is a small trade-off between the VGGNet and the suggested model in terms of accuracy and training time.

V. SUMMARY

The primary cause of death from skin cancer is the malignant lesion. Treatment can be possible if it is identified early. Deep learning techniques have been applied to identify cancer in literature.However each learner's performance is constrained. When making decisions on delicate topics like cancer, the performance can be improved by merging the opinions of different individual learners.

An ensemble model for the detection of skin cancer was created in this paper.
The three deep learning models of VGG, Caps-Net, and ResNet are combined to create it. The results show that with a classification training period of 106 seconds, the suggested ensemble attained an average accuracy of 93.5%. In terms of many quality metrics, such as sensitivity, accuracy, F-Score, specificity, false-positive, and precision, the suggested model outperforms individual learners. We plan to investigate the success of reinforcement learning-based methods for the identification of skin cancer in the future.

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