International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 11 Issue 3 ǁ March 2023 ǁ PP. 538-546

Combined Decision of Deep Learners for the Detection of Skin Cancer

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Abstract
Human cancer is a highly perilous disease resulting from genetic instability due to multiple molecular alterations. Skin cancer is the most prevalent type among various forms of human cancer. Our focus is on detecting malignant melanoma skin cancer, for which we employed deep learning techniques. Our approach involved training deep learning models on a database and using a CNN-based model for evaluation. This algorithm allows for easy detection of skin diseases in humans. By increasing the training data set, we can achieve more accurate results than the existing analyses.
Keywords: *Skin lesion, convolution neural network, combined decision, deep learning, ensemblelearning, skin cancer*

Date of Submission: 14-03-2023 Date of acceptance: 29-03-2023

I. INTRODUCTION

Skin cancers are a result of abnormal cell growth in the skin, with the potential to spread or invade other parts of the body. There are three primary types of skin cancers, namely basal-cell skin cancer (BCC), squalors cell skin cancer (SCC), and melanoma. Non-melanoma skin cancer (NMSC) encompasses the first two, along with other rare skin cancers. Basal-cell cancer develops slowly and can cause damage to surrounding tissues, but it seldom spreads to remote regions or leads to death. It frequently presents as a painless raised area of skin that appears shiny with small blood vessels, or as a raised area with an ulcer.

The human body's cells typically follow a structured life cycle, including creation, functional activity, and death, to ensure proper bodily function. However, when this order is disrupted, it can lead to the development of various diseases, including cancer.

Cancer can originate in any part of the human body, which comprises trillions of cells. In cancer, some cells in the body divide without inhibition and spread into surrounding tissues. Normally, human cells divide and multiply to produce new cells as needed by the body. During this process, cells grow, age, or become damaged, leading to cell death and replacement by new cells. However, cancer disrupts this systematic and precise cell cycle, leading to a drastic increase in abnormal and damaged cells. The survival of cells depends on the death of old cells, and new cells are produced only as required.

Skin cancer comprises various categories, including basal cell and squamous cell skin cancers, which are both classified as non-melanoma skin cancers. Non-melanoma skin cancer is highly treatable and has a low tendency to spread to other body parts. Melanoma is the most severe type of skin cancer. Malignant skin lesions are categorized into two types: melanocytic lesions, such as melanoma, and non-melanocytic lesions, such as basal cell carcinoma. Melanoma is the most aggressive and severe form of skin cancer, although it is less common than other types. If not diagnosed promptly, melanoma skin cancer can invade nearby tissues and spread to other parts of the body. The incidence of melanoma cases is increasing every year, with the Melanoma Foundation predicting 9,730 deaths due to melanoma in the United States and a 200% increase in cases, reaching 87,110 since 1973.

The limited availability of medical data has led to poor performance of deep learning models. Due to the lack of labeled medical images, researchers have turned to transfer learning approaches, which involve applying knowledge gained from solving one problem to another related problem. However, the performance of individual learners is limited, particularly in decision-making for sensitive issues such as cancer detection. Combining the decisions of individual learners can improve detection accuracy for skin cancer. The presented work developed an ensemble of deep learners, including VGGNet, CapsNet, and ResNet. The results indicate that the proposed ensemble model outperformed individual deep learners and achieved better accuracy in skin cancer detection.

II. LITERATURE REVIEW

2.1 Karl Thurnhofer-Hemsi, Enrique Domínguez [3] The diagnosis of skin diseases has become a challenging task in the medical field due to their visual similarities. While melanoma is the most well-known type of skin cancer, other skin pathologies have caused many deaths in recent years. The shortage of extensive datasets poses a significant obstacle in developing a dependable automated classification system. In this study, a deep learning framework for detecting skin cancer is introduced. Transfer learning was utilized to create plain and hierarchical classifiers (with two levels) using five advanced convolution neural networks. These classifiers can distinguish between seven types of moles with accuracy.

i. The main novelty of this network is the inverted residual with linear bottleneck, a procedure that eliminates non-linearity and maintains the representational power.
ii. The MobileNetV2 architecture consists of a total of 53 layers, with the first layer being a complete convolution layer, followed by 19 residual bottleneck layers.
iii. The premise of data augmentation is that a strong convolution neural network can be made invariant to translation, viewpoint, size, or illumination changes.

2.2 Md Shahin Ali, Md Sipon Miah, Jahurul Haque [6] Skin cancer, caused by damaged DNA that leads to uncontrolled cell growth, is one of the top three dangerous types of cancer that can result in death. Unfortunately, the incidence of this cancer is increasing rapidly. There have been efforts to use computerized analysis of skin lesion images to detect malignancy. However, this analysis is a challenging task due to various factors, such as light reflections from the skin surface, variations in color illumination, and different shapes and sizes of the lesions. Therefore, developing an automated skin cancer recognition system can provide valuable support to pathologists in the early stages, improving their accuracy and efficiency.

i. Melanoma is a type of skin cancer that can cause the development of malignant tumors on the skin. It acquired a better result in detecting of skin cancer.
ii. The use of DL based on a model-driven architecture allows for the rapid construction of models, which in turn enables quick predictions of results.
iii. The challenges associated with detecting skin cancer can be attributed to variations in image types and sources

2.3 Katja Hauser , Alexander Kurz [4] Deep neural networks (DNNs) are gaining popularity in medical applications due to their ability to solve complex problems. However, these algorithms use a black-box decision-making process, making it challenging for physicians to determine the reliability of the decisions. To address this issue, the use of explainable artificial intelligence (XAI) is often proposed as a solution.

i. Model fidelity is a feature of XAI methods that refers to how well the outputs of the method accurately reflect the internal workings of the classifier being explained.
ii. Certain XAI methods, like Guided Back propagation and Guided Grad CAM, are recognized for not being faithful to the explained model.
iii. There is a legal mandate that any software employed as a medical device must demonstrate an appropriate level of transparency.
iv. This article provides an overview of the XAI methods currently being developed for use in dermatological and dermatopathological assistance systems, and assesses their effectiveness.
v. XAI methods usually exhibit images that resemble the classified image or highlight specific areas within the image.

2.4 Mingjun Wei, QiweiWu [7] Skin disease is a significant public health concern worldwide, affecting a vast population. The symptoms of skin diseases are varied and may change over an extended period. It is challenging for the general public to identify the type of skin disease without medical assistance, and many individuals may overlook changes in their skin symptoms, leading to serious consequences such as permanent skin damage or even an increased risk of skin cancer. Early detection and treatment of skin cancer can significantly reduce morbidity and mortality.

i. CNN models have been extensively studied for the classification of skin diseases, and a number of these models have demonstrated excellent classification accuracy.
ii. Numerous scholars have suggested dependable convolutional neural network (CNN) models for multi-class classification.
iii. The input for skin lesion diagnosis in this model is skin lesion images and patient metadata, and it is a multi-class classification model.
iv. Image processing techniques such as image conversion, equalization, enhancement and segmentation can be used to improve the accuracy of image classification.

2.5 Jeremy Kawahara, and Ghassan Hamarneh [2] We suggest that accurate classification of skin lesions is crucial for effective treatment. To achieve this, we propose a new convolutional neural network (CNN) architecture for skin lesion classification that is capable of learning from information obtained from multiple image resolutions and leveraging pre-trained CNNs. Unlike traditional CNNs that are usually trained on single resolution images, our CNN consists of multiple tracts, where each tract simultaneously analyzes the image at a different resolution and learns interactions across multiple image resolutions using the same field-of-view. We modify a single resolution pre-trained CNN to work with multi-resolution input, and fine-tune the entire network using a fully learned end-to-end optimization with auxiliary loss functions.

i. Accurate classification of various types of skin lesions is essential for determining appropriate treatment, and computer-based systems that classify skin lesions from skin images may serve as an important screening or second opinion tool.
ii. The focus of Regenerate Response is to predict multiple types of skin lesions, including both melanoma and non-melanoma cancers.
iii. However, the simple aggregation approach does not learn the interactions among different resolutions.
iv. The prediction is solely dependent on a single input resolution, and there is no consideration of interactions across multiple input image resolutions.

2.6 Li-sheng Wei , Quan Gan, and Tao Ji [5] The skin is the largest organ in the human body, consisting of the epidermis, dermis, and subcutaneous tissues. It is equipped with blood vessels, lymphatic vessels, nerves, and muscles, enabling it to sweat, sense external temperatures, and shield the body. The skin covers the entire body, providing protection against external threats, including artificial and chemical damage, harmful viruses, and the body's own immune system. Additionally, the skin maintains a balance of lipids and water in the epidermis and dermis, stabilizing its barrier function.

i. The utilization of image rotation and segmentation enables the transformation of an image into a more significant and simpler format, facilitating its analysis.
ii. The third stage involves identifying three different types of skin diseases based on the features obtained using SVM.
iii. It is necessary to perform median filtering on the images to reduce the impact of irrelevant background on skin segmentation and identification.
iv. Through experimentation, the texture parameter for contrast of normal skin, herpes, pimples, and psoriasis can be obtained and illustrated.

2.7 Balazs Harangi [1] To achieve high classification accuracy, we have combined the outputs of the classification layers of four distinct deep neural network architectures. We propose an aggregation approach for robust convolution neural networks (CNNs) to be integrated into a single framework, where the final classification is based on the weighted output of the member CNNs. We have considered various fusion-based methods for aggregation and selected the best performing one for this task. Our experimental results demonstrate that creating an ensemble of different neural networks is a valuable approach, as each fusion strategy outperforms individual networks in terms of classification accuracy.

i. One of the advantages of CNNs is that they can surpass a human expert in classifying a task, given that they undergo extensive learning on a large annotated training dataset.
ii. Generally speaking, aggregating the opinions of experts enhances the accuracy of predictions.
iii. We need to train or fine-tune the CNNs before creating an ensemble of them.
iv. The task for the competition was to develop automated methods that can classify skin lesion images as either nevus, melanoma, or seborrhea kurtosis.
v. We have modified the SVM model for two main reasons: firstly, to allow the members to vote for their strongest candidate classes based on their confidence levels, and secondly, to improve the performance of the model.

III. PROPOSED METHODOLOGY

The deep learning-based ensemble approach presented here is a two-stage process. First, three deep learning models, namely VGG, CapsNet, and ResNet, are developed using malignant and benign images from the International Skin Imaging Collaboration (ISIC) skin cancer images repository. In the second stage, the decision of the deep learners is combined using majority weighting.

I. **Loading of data set:** To save a SKIN image in your database, you need to create a storage item, which is the same process as storing a photo. The data set was collected from online websites.
II. **Pre-process:** Pre-processing of image data involves improving the quality of images by suppressing undesired distortions or enhancing important image features for further processing. This can include

geometric transformations like resizing and conversions, which are typically considered part of pre-processing methods.

3.1 DATASET: To store all the data in data base to identify the accurate result.

The International Skin Imaging Collaboration (ISIC) image repository was the source of the dataset which includes cancerous and non-cancerous images. ISIC is a collaborative effort between academia and industry aimed at supporting the development of digital skin imaging applications for the early detection of melanoma to reduce its life cycle.

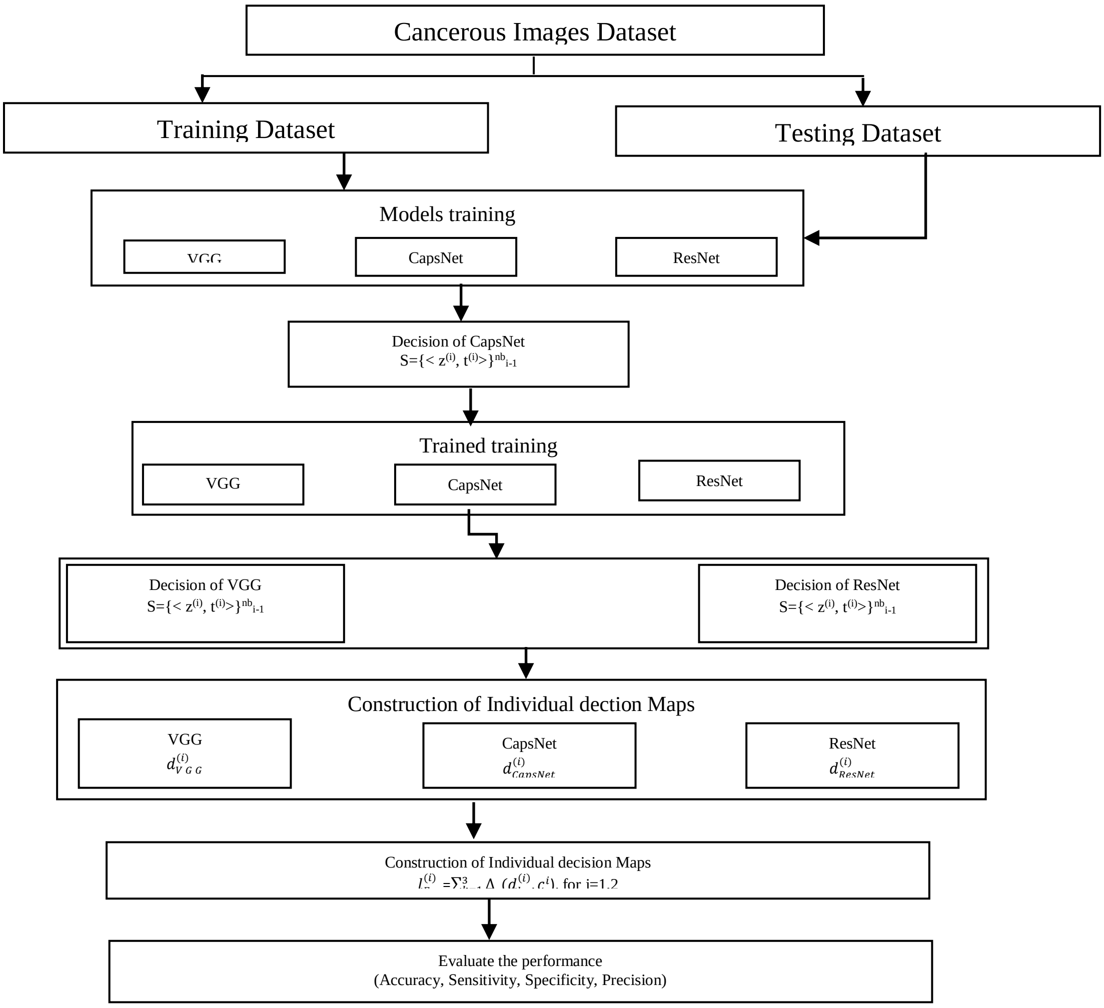

Figure 1: Block diagram

3.2 DEEP NEURAL NETWORK

I. **VGG16:** The VGGNet model is one of the most commonly utilized CNN models. It is popular due to its simplicity, ease of use, and the incorporation of small-sized convolution kernels, which make it a preferred deep learning model.

II. **CAPSULE NETWORK (CapsNet):** Convolution neural networks have been very successful in deep learning areas. There are many properties of convolution neural networks that are contrary to the human brain and make them work ineffectively.

1. $$\mathrm{x} = x_{0,k} + \sum_{s=1}^{a} \sum_{t=1}^{a} \mathrm{w}_{\mathrm{k,s,t}} \ \mathrm{x}^{(\mathrm{i+s,j+1})}$$

III. **RESNET:** The deep neural network model utilizes residual learning and includes convolution and pooling layers that are stacked on top of each other and fully connected.

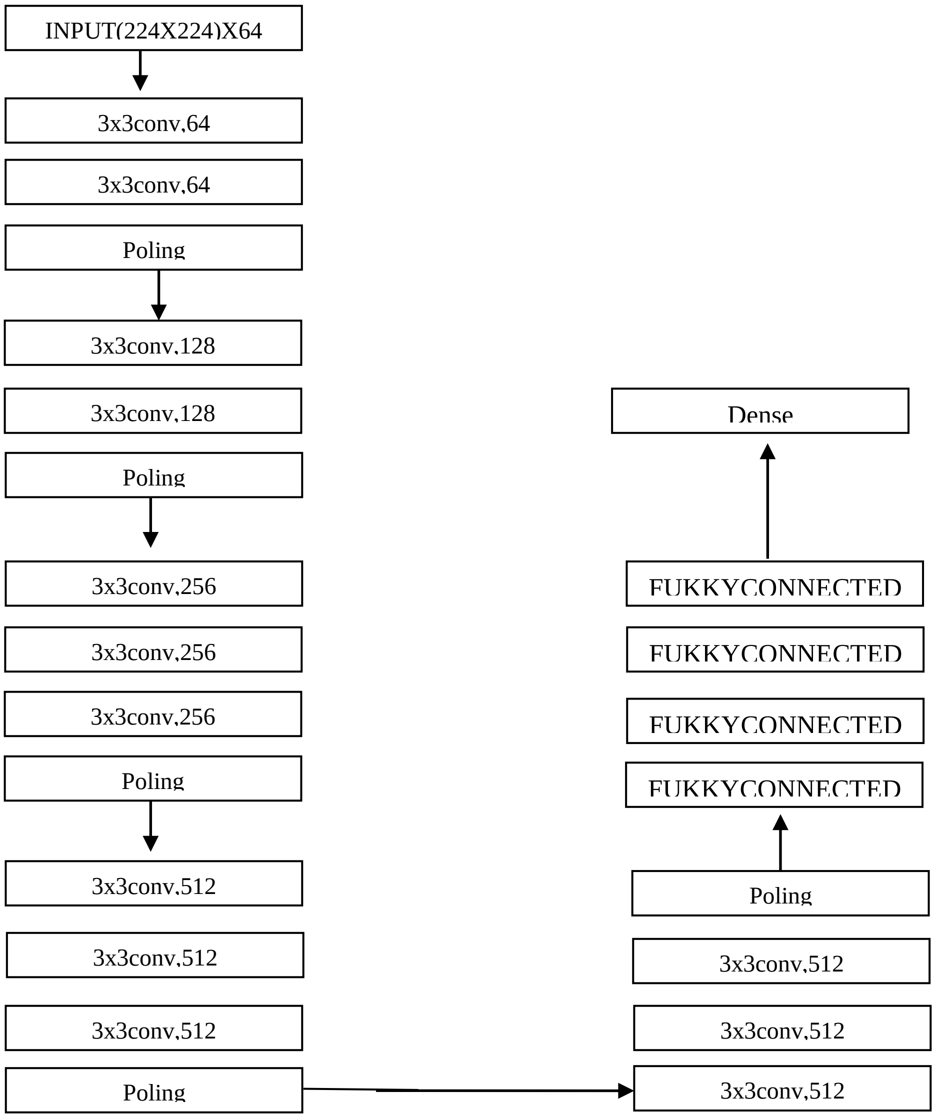

Figure 2: VGG16 Block diagram

The ResNet layers are divided into four parts, as depicted. The initial convolution layers include filters of size 7 x 7 and 3 x 3, followed by max-pooling. The first group is comprised of three additional parts or residual blocks, each sub-block containing three convolution layers with kernel size.

IV. PROPOSED ENSEMBLE MODEL

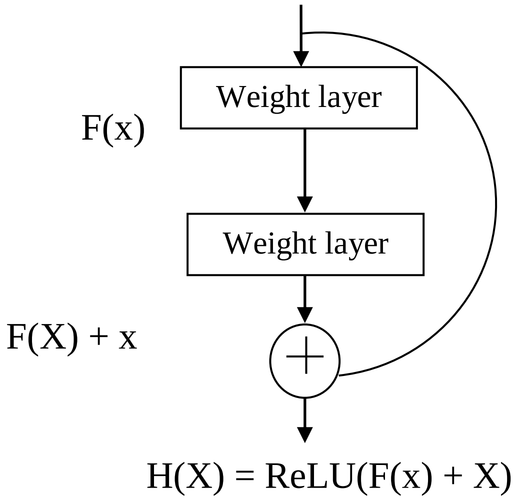

Figure 3: Deep residual network residual block.

V DIFFERENT MEASURES USED TO EVALUATE PERFORMANCE

The performance of the proposed technique was evaluated using the following quality measures:

i. **ACCURACY:** The accuracy measures the classifier's capability to predict the correct class labels, and it is computed as follows:

$$\textbf{Accuracy}=\frac{TN+TP}{NF+FP+TN+TP}$$

ii. **SENSITIVITY:** Sensitivity and specificity are widely used parameters in medical and epidemiological research, but many statisticians in mathematical fields may not be familiar with them. They evaluate the classifier's ability to correctly predict the positive class. Sensitivity is calculated by the following formula.

iii. **SPECIFICITY:** Specificity is a performance measure used to evaluate the ability of a classifier to correctly predict the negative class. It measures the proportion of actual negative cases that are correctly identified as negative by the classifier.

iv. **F-SCORE:** The F-score is employed to evaluate statistical tests and it utilizes Recall and Precision to compute the prediction accuracy. The F-score can also be measured using the weighted average of recall and precision. Recall is calculated by dividing the number of correct predictions by the total number of predictions.

v. **CONFUSION MATRIX:** A confusion matrix reflects the accuracy and inaccuracy of a machine learning algorithm. The size of the confusion matrix is determined by the number of items to be predicted.

		Predicted Class	
		P	**N**
Actual Class	**P**	True Positive (TP)	False Negative (FN)
	T	False Positive (FP)	True Negative (TN)

Figure 4: Confusion Matrix

VI Models

i. **Feature extraction:** To obtain meaningful results while retaining the information in the original dataset, raw data is converted into numerical features through a process known as feature extraction. This approach is superior to directly applying machine learning algorithms to raw data..

ii. **Train and test data:** The Train/Test technique is a way of evaluating the performance of a model. It involves dividing the dataset into two parts: a training set and a testing set, usually with a split of 80% for training and 20% for testing. The model is trained using the training set.

iii. **Algorithm:** A CNN is a type of deep learning network architecture designed for tasks involving pixel data and image recognition. While there are various neural network types in deep learning, CNNs are preferred for object identification and recognition. In this case, we utilized CNNs for training and verifying fingerprint data.

VII. RESULTS AND DISCUSSION

The evaluation of the suggested model's performance, which includes individual deep learners and an ensemble system based on deep learners, was conducted in the study. Additionally, the proposed approach's results were compared to those of individual machine learning approaches developed in the same study. According to Table 1, VGG, CapsNet, and ResNet achieved accuracy values of 79%, 75%, and 69%, respectively.

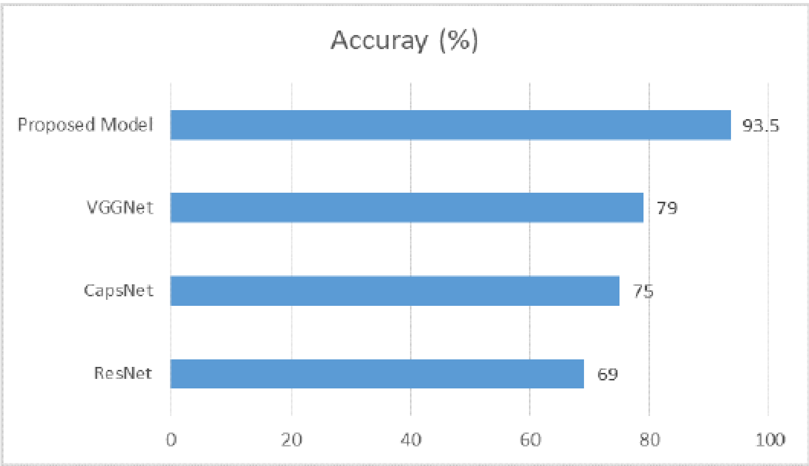

Figure 5: Proposed model

Table compares the performance of various deep learning models with the proposed model. It can be observed. that the proposed model has outperformed state-of- the art methods in terms of various performance metrics such as accuracy, sensitivity, specificity, etc.

Table 1 : 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
Naïve Bays	45.62	43.86	44.4	45.25
Proposed Ensemble	93.50	94.0	87.0	92.0

7.1 Accuracy of VGG16

A confusion matrix represents the righteousness and falsehood of a machine learning algorithm. The confusion matrix of VGG is shown It is noticed from the figure that the VGG model has more classification errors in the No-cancerous class.

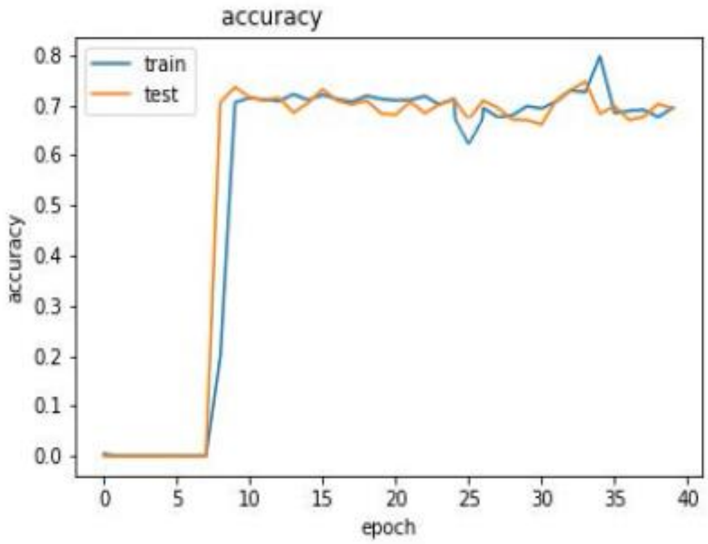

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Figure 6: Accuracy of VGG16

VIII ABLATION STUDY

The training time for classification of VGGNet, CapsNet, ResNet, and the proposed method is 106s, 136s, 188s, and 109s, respectively. The different models are graphically illustrated. There is a slight trade-off between VGGNet and the proposed model in terms of accuracy and training time. However, the proposed model is more advantageous due to its higher performance difference.

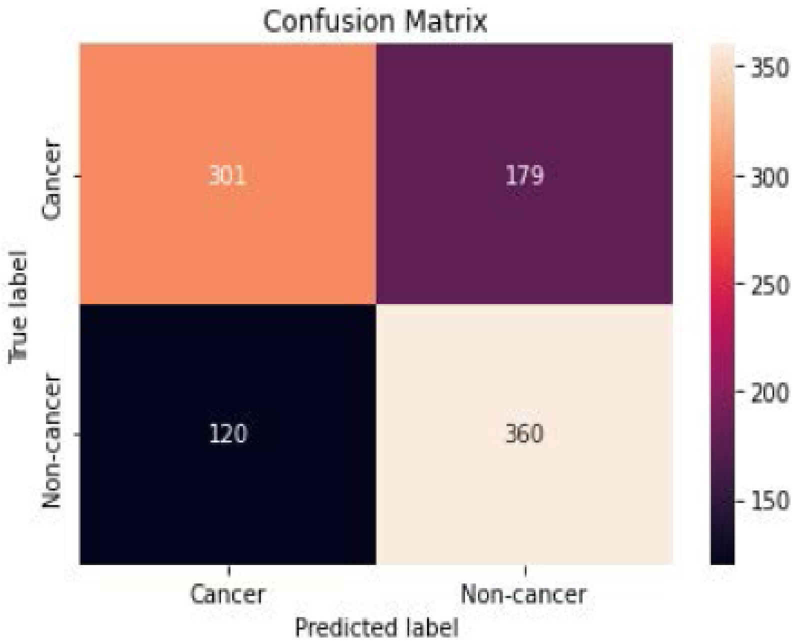

Figure 7: CapsNet confusion matrix.

Ensemble network confusion matrix.

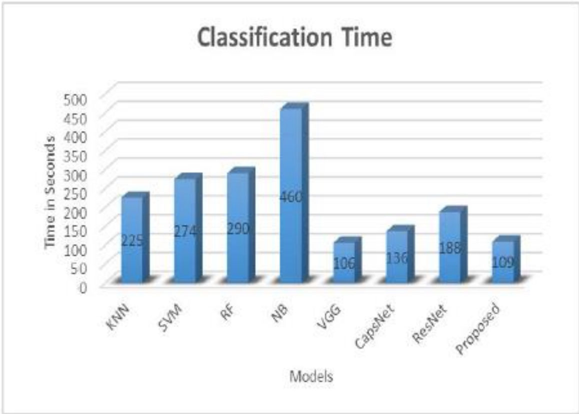

Figure 8: Confusion matrix.

IX. CONCLUSION

Skin cancer is a major cause of death, especially when it is in the malignant lesion stage. Early diagnosis is crucial for effective treatment. Although deep learning approaches have been used to detect cancer, the performance of individual learners is often limited. To improve performance, the decision of diverse individual learners can be combined for decision-making on sensitive issues such as cancer. In this paper, an ensemble model was developed to detect skin cancer.

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