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Research Article

Detection and Classification of Skin Cancer by using CNN-Enabled Cloud Storage Data Access Control Algorithm based on Blockchain Technology

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Abstract: Skin cancer is one of the most serious problems in the world. In the circumstance of manual examination by a clinic, the human eye is unable to detect disorders. In this research paper I will discuss the deep learning techniques that help to solve the problem of skin cancer. Skin cancer disease is similar to optical properties that choose the useful feature of images. It's accurate detection and classification of skin disease through images using CNN (Convolutional Neural Network). We used popular datasets to evaluate the performance of our proposed model. Specifically, the model achieves an accuracy of 99.3% on the skin cancer dataset. The aim of this paper is first detection and classification of skin cancer. Secondly, apply the preprocessing technique of skin cancer dataset to find the accuracy of skin cancer disease.

Keywords: Convolution Neural Network; Preprocessing; Image Classification; Skin Cancer; Health Risks

1. Introduction

Skin cancer is a serious problem that frequently spreads in the environment. In the human eye, it is unable to detect the disorder. In our daily life, deep learning techniques are used to solve the problem. These techniques also used automated and computerized mechanisms to detect skin cancer [1]. It performs various tasks. There are three types of skin cancer. Base cell skin cancer, squamous cell skin cancer, and the third one is melanoma. In researchers' research, they conclude that UV radiation from the sun causes major skin cancer. It has been the most common disease in the environment [2].

In the United States, 46,000 cases are reported each year. Computer-based technology makes it possible to detected skin cancer easily. The most common algorithm for classification is Convolutional Neural network (CNN). This algorithm easily detects skin cancer.

CNN is a deep learning algorithm that applies to image datasets. CNN generate the model. This model is very efficient to solve the problem [3]. CNN commonly consists of three layers. The Convolutional layer, maxpool layer and the third is fully connected layer [3].

2. Literature review

The authors compare the transfer learning model for detecting skin cancer, Conventional Neural Network (CNN) performs the best algorithm to detect skin cancer. This paper also discusses calculating the F1 Score, Recall, accuracy and precision. The seven transfer learning models are: DenseNet201, InseptionResnetV2, MobileNetV2, InceptionV3, ResNet50, DenseNet169, and VGG16. Now calculate the higher accuracy to find the skin detection easily [1]. This paper also diagnoses skin disease with deep learning. Different public datasets are used to detect the different types of skin cancer by deep network architecture like: ResNet, Darknet, Faster R-CNN etc. [2]. Similarly, authors in [3] discuss the different methods and techniques to identify and classify skin cancer. Convolutional Neural Network (CNN) is a faster and most efficient deep learning strategy to detect the features of skin cancer. This paper discusses the two pre-trained CNN models, VGG-16 and ResNet50. Both models used ImageNet datasets to extract the features of skin cancer. Also, detect skin cancer segmentation by using DL approaches, especially region-based Convolutional Neural Network (RCNN) and Fuzzy K-mean clustering (FKM). Finally, the conclusion is that RCNN extracts faster than FKM [4]. This paper discusses state-of-art machine learning techniques that are used to detect skin cancer. Support Vector Machine (SVM), and Convolutional Neural Networks (CNN) algorithms. Different methods and datasets are used to detect accuracy, sensitivity and specificity of the skin cancer classification using CNN [5]. This paper discusses skin lesion analysis using deep learning techniques. Pre-processing and segmented images results in better classification performance of skin lesion image. This paper discusses comparative analysis of convolutional and deep learning techniques [6]. This paper discusses the supervised and unsupervised learning, Convolutional Neural Network (CNN) model used to detect and classify skin cancer. DarkNet-169 and ResNet50 are used to train the model to obtain results [7,8].

The rest of the paper consists of few sections. The next section 3 presents materials and methods; section 4 presents proposed methodology, section 5 exhibits results and their analysis. Finally, section 5 concludes research.

3. Materials and Methods

3.1 Dataset

Skin cancer ISIC The International Skin Imaging Collaboration dataset is used. In this dataset test and train two folders, each folder has 9 directories. In the test dataset, the total images were 144. In the train dataset, the total images are 2,239. Overall images are 2,383 [9].

3.2 Preprocessing

Preprocessing is the very first step after obtaining the datasets. An image is composed of the bulk of pixels. Pixels fix themselves in a particular position. Pixels are separate over the entries image in the form of matrix [10]. Pixels represented a unique variety of color. Many objects are shown in a single image, out of which the object of interest is only needed [11]. Different objects of interest vary with the domain of work. Like work on object detection and then classifying of single images [12]. The processing process covers image data cleaning in such a way that Only requires useful piece of data is left behind. An image is compacted and refined. Computer vision reduces human intervention in visualizing the object detection and classification of single images [13]. It detects the image visualization in different objects from physically to digitally. There are various kinds of strategies available for image processing [14]. Some of them reduce noise reduction, remote sensing, edge detection, neural preprocessing and many more. Output is forwarded to the downstream task. Preprocessing steps are as follows: cleaning of data means removing noise elements in the data of an image and also reducing the negative effect of the image [15]. Normalization: Scaling the data according to features of image. Smoothing: Applying filtering techniques to reduce the noise of the data of the images [16]. Feature Extraction: identifying and selection of important features of an image, and it also transforms the Raw-data and retains the important information [17,18].

3.3 Features extraction

A feature is an image that defines its characteristics, structure and content, an important parameter in the image that has been used for classification and object recognition [10]. Feature extraction highlights the interesting part of an image. One important point related to feature extraction points still remains under study to extract ideal features [15]. The result obtained in feature extraction depends on the needs and interest of the working domain [17]. There are countless numbers of features available in an image. But the only required feature patterns is the function of feature extraction [18]. Different kinds of features like color, contrast, text, correlation, shape, homogeneity and many more are drawn out by various accessible feature extraction approaches [15]. The most common feature extraction strategies are used in the literature, such as grey level, filter based, and analysis of component [15]. These strategies further provide some algorithms to follow in different domains [12]. In single object detection and classification [16]. Feature extraction of images is used to reduce a huge input dataset with similar features. A large number of datasets are variables for computing the processing of images [18]. Feature extraction of different images, the methods and variables select the features that reduce the data should be accurate and describing complete the original dataset of images [17].

3.4 Disease detection

Disease detection is the second step after the preprocessing of a computer-aided diagnosis system. This step is done for skin cancer disease. Computer Aided Diagnosis (CAD) is an innovation in image processing with machine learning, using artificial intelligence (AI) techniques. These systems are playing a very helpful role in the medical field. They aid agronomists with early skin cancer disease detection. This structure is described as an innovation of machine learning because they tend to process massive data to draw new conclusions from the data and improve their diagnostics. It brings together experts from two fields of biology and computer science. They start becoming assistants at diagnosing diseases. Such paradigms are becoming more in demand because they tend to improve accuracy and time in detecting diseases and making as less human intervention as possible. This prototype passes the dataset of images to be detected through the pipeline of a collective set of processes.

3.5 Feature selection and classification

After the operations of gathering and arranging a set of features, some features are selected to make the model ready for the classification scheme. It assists the proposed model towards optimization in such a way that it includes non- redundant and fully relevant features. It does so from the basic feature vector because it saves the cost of computing unconsumed features. This feature mining composed of two phases. One is to produce feature subtitles from an input feature set coming from feature fusion. The second one is to determine if the formed subset is optimal or not. Hence, it leads the model to raise its classification accuracy and crucially diminish the computational time.

4. Proposed methodology

After dealing with and preparation of dataset, data becomes ready to build a Computer Aided Diagnosis (CAD) system. This prototype comprises a group of integrated processes that runs the image samples to be detected. This research article is aimed at providing solutions to agronomists for detection of skin cancer disease. A variety of deep networks handle large and complex data efficiently. While working with imaging in the domain of computer vision, Convolutional neural-network (CNN) is chosen. CNNs have proved to be powerful tools in semantic segmentation, transfer learning, object detection, visual recognition, image classification, video analysis, improving efficiency and many more [8].

ALGORITHM 1: ATTENTION-BASED META-CNN FOR SKIN CANCER DETECTION AND CLASSIFICATION

Input: Skin cancer ISIC The International Skin Imaging Collaboration

Output: Detection and Classification

1. **Preprocessing Phase:**
   - Cleaning of data means removing noise elements in the data of an image and also reducing the negative effect of the image
   - Normalization: Scaling the data according to features of image.
   - Smoothing: Applying filtering techniques to reduce the noise of the data of the images
2. **Feature Extraction Using Base CNNs:**
   - Initialize: Proposed itself CNN models:

     Base CNN 1: ResNet-65
   - Apply Global Average Pooling (GAP) to reduce dimensionality:

     $Fvgg = GAP\ (F1)$, $F\text{res} = GAP\ (F1)$, $F\text{dense} = GAP\ (F1)$
3. **Meta-CNN Classification:**
   - Pass Fmeta through a multi-path dense layer architecture:

     Path 1: Conv2D (512) → ReLU → Dropout (0.5)

     Path 2: Conv2D (256) → BatchNorm → ReLU → Dropout (0.4)

     Path 3: Conv2D (128) → ReLU 4.2
   - Concatenate outputs from all paths:

     $$F_{\text{dense}} = Path1\ (F_{\text{meta}}) \oplus Path2\ (F_{\text{meta}}) \oplus Path3\ (F_{\text{meta}})$$
   - Apply the output softmax layer for final classification:

     $$\boldsymbol{y} = \boldsymbol{softmax}\ (\boldsymbol{W} \cdot \boldsymbol{F}_{\text{dense}} + \boldsymbol{b})$$
4. **Training Phase:**
   - Use the Hybrid Loss Function:

     $$\mathscr{L} = \alpha \cdot \text{Binary Cross-Entropy} + (1 - \alpha) \cdot \text{Focal Loss}$$

     (Set $\alpha = 0.7$ to balance the loss components.)
   - Optimize the model using the Adam optimizer with a learning rate decay:

$$\boldsymbol{\eta} = \boldsymbol{\eta}\mathbf{0} \cdot \mathbf{1}\ /\mathbf{1} + \boldsymbol{\gamma} \cdot \boldsymbol{t}\ ,\ (\boldsymbol{\eta}\mathbf{0} = \mathbf{0.001},\ \boldsymbol{\gamma} = \mathbf{0.01})$$

- Applied early stopping to prevent overfitting based on validation loss.

5. **Evaluation:**
   - Evaluate the model performance using:
     1. Accuracy, Precision, Recall, and F1-Score Confusion Matrix

CNN is widely and rapidly maintaining its position in image analysis. Here, CNN is used specifically to detect, recognize, and classify the disease. Main key features of CNN are:

- Convolutional layers
- Pooling layers
- Activation function
- Fully connected layers
- Output layers

ResNet: Residual neural network is abbreviated as ResNet. Residual blocks assembled in a manner are called a residual network. It's a CNN-based network. Its performance and depth is directly proportional to the number of residual blocks as shown in Figure 1.

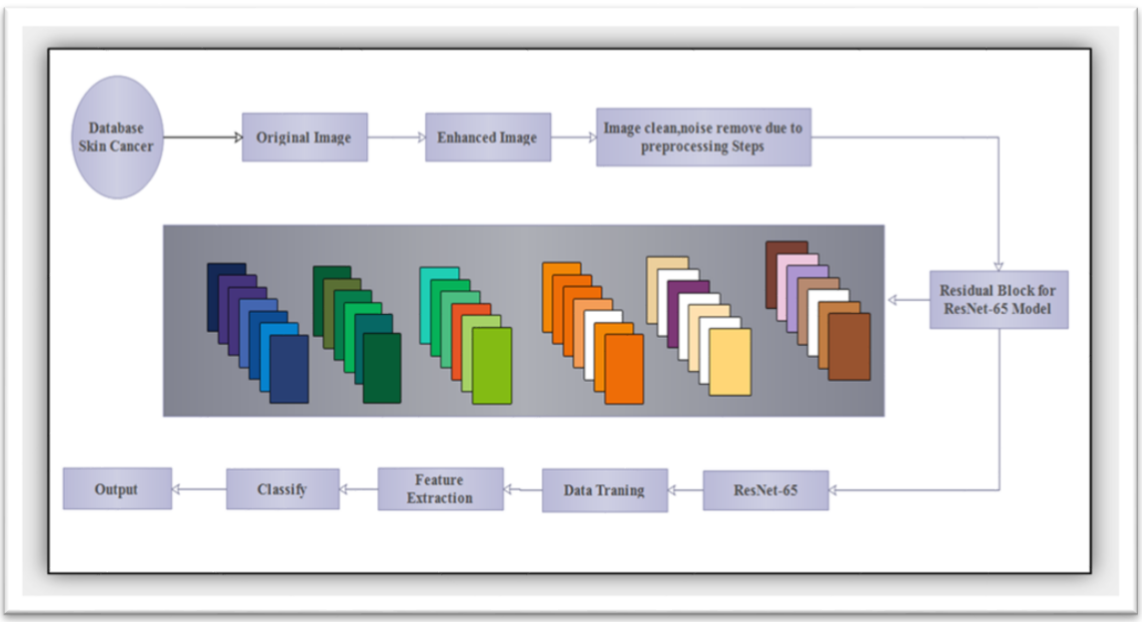

Figure 1: Proposed research framework

4.2 Proposed architecture

There are various structures of ResNet framed with different numbers of layers and several blocks. The proposed architecture is formed using an existing idea of a residual network in MATLAB 2023a. It comprises 65 layers, 68 connections, 151M learnable, 6 residual blocks, 1 initialization block, 1 final block, and 5 additional blocks. Initial block takes an input image with input size 256x256x3. All the sample images are resized to this range so that the model would get all samples if the same range or size. This is the transformation step required before moving towards training while preserving the original information.

Then passes the data to convolution layer with filter size 3x3, stride as 2, and number of filters are 32. Max pooling layer have the pool size as 3x3 and stride 1. Its structure can be seen in Figure 2 and 3.

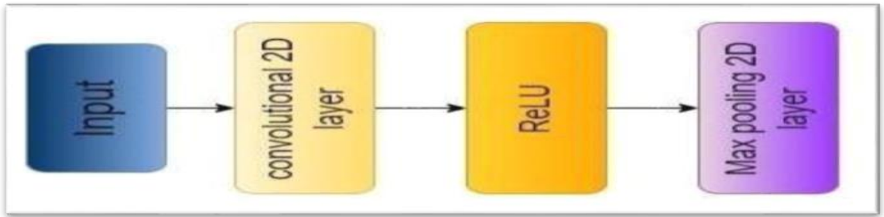

Figure 3: Proposed initial block

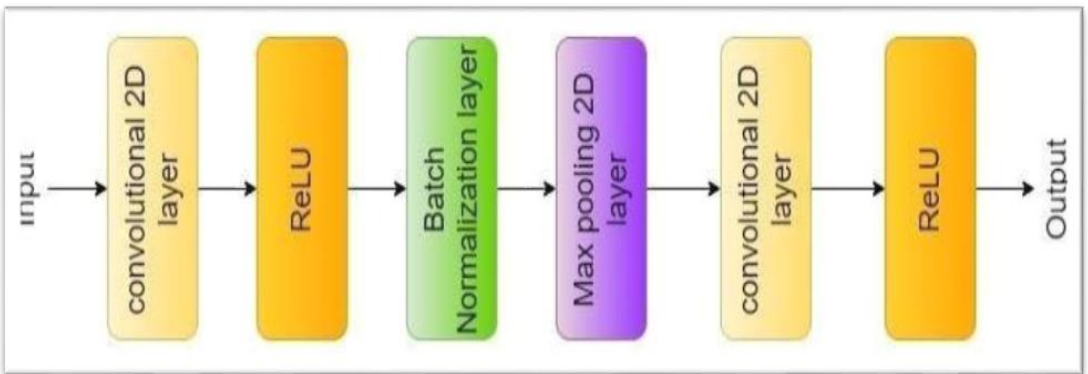

Figure 4: Proposed residual block

It follows the mathematical expression as; H(x) = F(x)+x. Where H(x) is the residual mapping, x is the input, and F(x) is the function performed by the layers. F(x)+x is an element wise addition performed by residual blocks. F(x)+x produces an output H(x). Afterwards ReLU is applied to H(x). This H(x) produced by a residual block is produced by an element wise addition. In case of any missing value, it adds the original input "x" into it directly and can skip some layers in between. By skipping some layers, residual connections give alternative way for input "x" to reach later regions of the neural network. In the proposed architecture, there are 6 blocks that produces the value H(x) as shown in Figure 4.

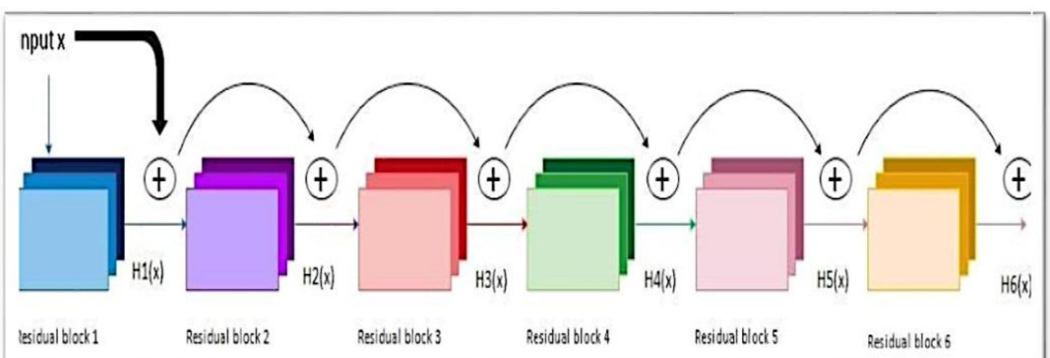

Figure 4: Proposed architecture

Addition blocks are used to add the outputs coming from residual blocks. All five addition blocks follow the same structure as shown in Figure 5 and 6. Table 1 shows values of parameters in residual blocks (ResNet65)

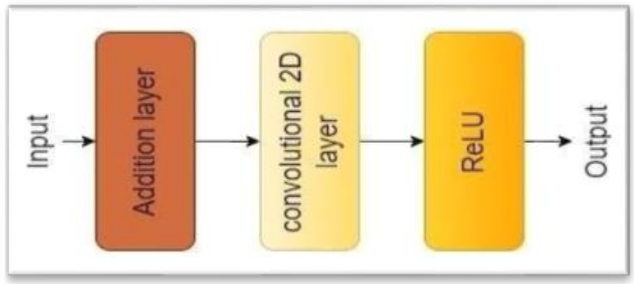

Figure 5: Additional Block

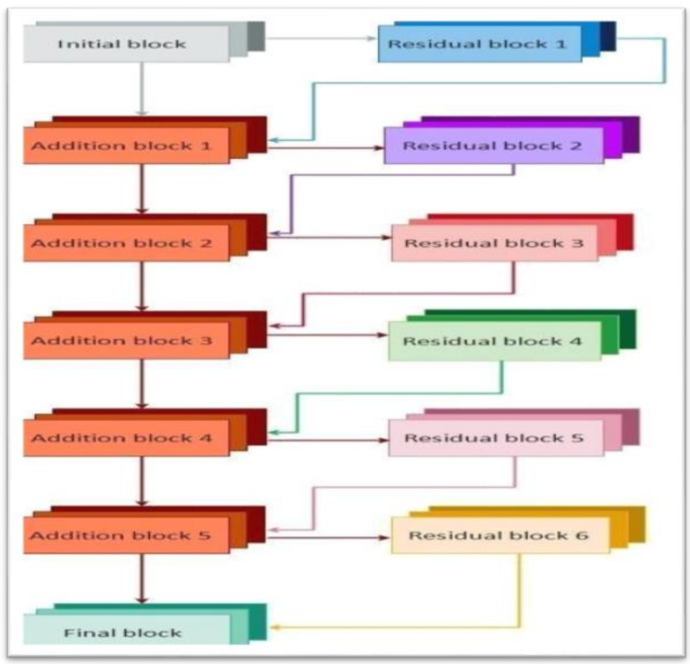

Figure 6: proposed Architecture

Table 1: Changing values of parameter in residual blocks (ResNet65)

Block	Layers	Size/Stride	No. of Filter
Residual block 1	Conv2D	3x3/2	32
	Relu		
	Batch Normalization		
	Max Pooling		
	Conv2D	3x3/1	64
	Relu		
Residual block 2	Conv2D	5x5/2	64
	Relu		
	Batch Normalization		

	Max Pooling		
	Conv2D	3x3/1	128
	Relu		
Residual block 3	Conv2D	3x3/1	128
	Relu		
	Batch Normalization		
	Max Pooling		
	Conv2D	3x3/2	256
	Relu		
Residual block 4	Conv2D	3x3/1	256
	Relu		
	Batch Normalization		
	Max Pooling		
	Conv2D	3x3/1	512
	Relu		
Residual block 5	Conv2D	3x3/2	512
	Relu		
	Batch Normalization		
	Max Pooling		
	Conv2D	3x3/1	1024
	Relu		
Residual block 6	Conv2D	3x3/1	1024
	Relu		
	Batch Normalization		
	Max Pooling		
	Conv2D	3x3/2	2048
	Relu		

5. Results and analysis

The 24000 WCE images are included in the experimental method for classifying. Cubic SVM, Cubic KNN, Medium Neural Network, Trilayered Neural Network, Bilayered Neural Network, and Wide Neural Network are the ten classifiers that have been employed. For training, 70% of data is utilized while the remaining 30% is utilized for testing purposes and ten cross validations have been performed. The system on which we performed the experiment is Core i5, with 8 GB RAM and 8 GB graphics card. MATLAB 2023a is used for coding.

5.1 Experiment (70/30 cross validation)

In the experiment, use Feature Extraction to select the original feature. These features are extracted for the purposes of testing, and then their performance is evaluated using five performance measures: Precision (PPV), Sensitivity, Accuracy, F1Score, and Time. The results show that broad Neural Network has the maximum accuracy of 99.7% exhibited in Table 2.

Table 2: Classification accuracy of original feature vector (ResNet-65)

Classifier	Precision (PPV%)	Sensitivity (TPR%)	Accuracy (%)	F1 Score	Time (sec)
Narrow Neural Network	96	97	97.0	3	3630.3
Medium Neural Network	97.1	99.4	99.4	0.6	384.89
Wide Neural Network	**99.3**	**99.5**	**99.7**	**0.3**	**458.06**
Bilayered Neural Network	94.8	95.8	95.8	4.2	6188.6
Trilayered Neural Network	94	95	95.0	5	5016.7
Cubic SVM	98.3	99.3	94.3	0.7	1123.8
Cubic KNN	94.3	95.3	95.3	4.7	14382

While the other extracted evolution measures of the Wide Neural Network, are a sensitivity rate of 99.5%, the Precision rate of 99.3%, F1Score is 0.3, and the computational time is 458.06 (sec). The second-highest accuracy achieved is 99.4% for Medium Neural Network. The other measures for Medium Neural Network are 99.4%, 97.1%, 0.6. 384.89 (sec), respectively. The rest of the remaining classifiers- Narrow Neural Network, Bilayered Neural Network, Trilayered Neural Network, Cubic SVM, Cubic KNN achieved an accuracy of 97.0%, 95.8%, 95.0%, 99.3%, 95.3% respectively.

5.2 Trade-offs between accuracy and computation time

Different classifier performances are mentioned in numerical in Table 2. Some classifiers perform better, and accuracy should be higher because they capture more complex features in the resNet-65 model (design itself). This model also required more computation and training time. But the pretrained CNN model of Matlab, for example, Resnet-50, Desnet, EfficientNetB0, B1 etc. These models were faster and more efficient, but their accuracy was comparatively lower as shown in Figure 7.

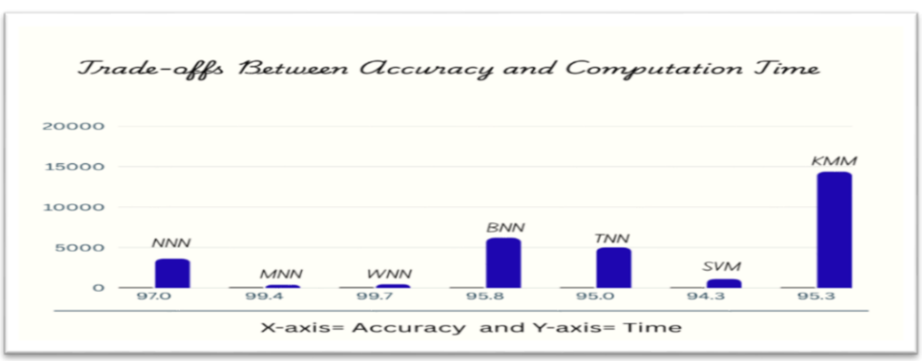

Figure 7: Trade-offs between accuracy and computation time

In this graph show trade-offs between accuracy and computation time X-axis show Accuracy values and Y-axis show time. In all classifiers, accuracy should be efficient, but time and F1-Score should be vary. Almost all classifiers, time should be higher, but in classifier Wide Neural Network is higher accuracy

(99.7%) but time and F1-Score should be less. That's why choose this classifier for better performance. The results are exhibited in Figure 8, 9, 10, 11, 12.

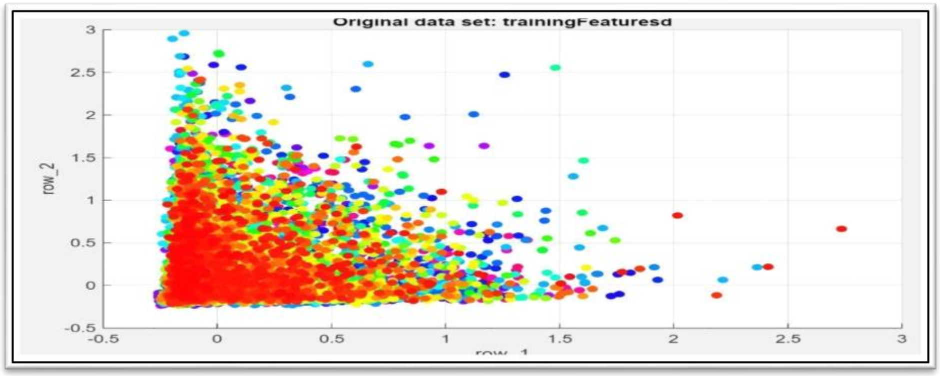

Figure 8: Scatter plot of training feature

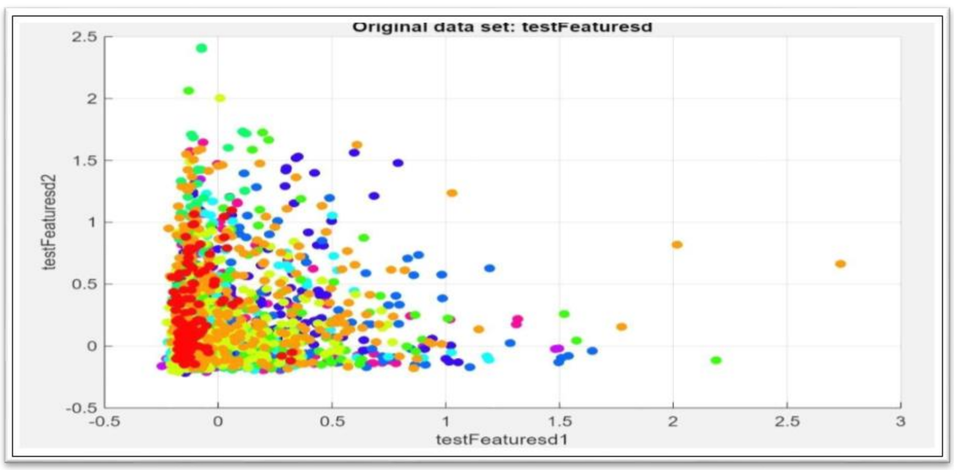

Figure 9: Scatter plot of testing feature

5.3 Experiments (50/50 cross validation)

In the experiment, use Feature Extraction to select the original feature. These features are extracted for the purposes of testing, and then their performance is evaluated using five performance measures: Precision (PPV), Sensitivity, Accuracy, F1Score, and Time. The results show that broad Neural Network has the maximum accuracy of 97.0%. While the other extracted evolution measures of the Wide Neural Network, are a sensitivity rate of 97.5%, the Precision rate of 97.3%, F1Score is 2.4, and the computational time is 213.06 (sec). The second-highest accuracy achieved is 97.2% for Cubic SVM. The other measures Cubic SVM are 97.3%, 96.3%, 2.8 6434.9 (sec), respectively. The rest of the remaining classifiers- Narrow Neural Network, Bilayered Neural Network, Trilayered Neural Network, Cubic KNN achieved an accuracy of 97.0%, 96.2%, 96.3%, 95.3%, 95.9% respectively. The classification accuracy of original feature vector is shown in Table 3.

Table 3: Classification accuracy of original feature vector (ResNet-65)

Classifier	Precision (PPV%)	Sensitivity (TPR%)	Accuracy (%)	F1 Score	Time (sec)
Narrow Neural Network	96	97	97.0	3	88.303
Medium Neural Network	97.1	96.4	96.2	3.8	1292.8
Wide Neural Network	**97.3**	**97.5**	**97.6**	**2.4**	**213.06**
Bilayered Neural Network	94.8	95.8	96.3	3.7	1838.7
Trilayered Neural Network	94	95	95.3	4.7	1838.7
Cubic SVM	96.3	97.3	97.2	2.8	6434.9
Cubic KNN	94.3	95.3	95.9	4.1	1905.5

5.4 Trade-offs between Accuracy and Computation Time (50/50 Cross Validation)

Different classifier performances are mentioned in numerical in Table 3. Some classifiers perform better, and accuracy should be higher because they capture more complex features in the resNet-65 model (design itself). This model also required more computation and training time. But the pre-trained CNN model of Matlab, for example, Resnet-50, Desnet, EfficientNetB0, B1 etc. These models were faster and more efficient, but their accuracy was comparatively lower.

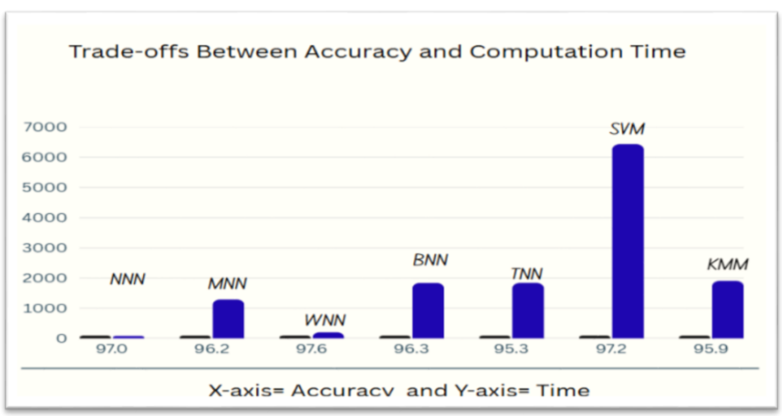

Figure 10: Trade-offs between accuracy and computation time

In this graph show trade-offs between accuracy and computation time X-axis show Accuracy values and Y-axis show time. In all classifiers, accuracy should be efficient, but time and F1-Score should vary. Almost all classifiers, time should be higher, but in classifier Wide Neural Network is higher accuracy (97.6%) but time and F1-Score should be less. That's why choose this classifier for better performance. Comparison of proposed model with existing techniques is presented in Table 4.

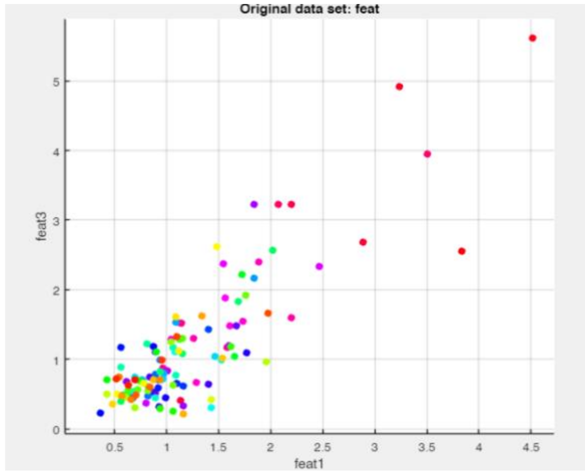

Figure 11: Scatter plot of training feature (50/50 Cross Validation)

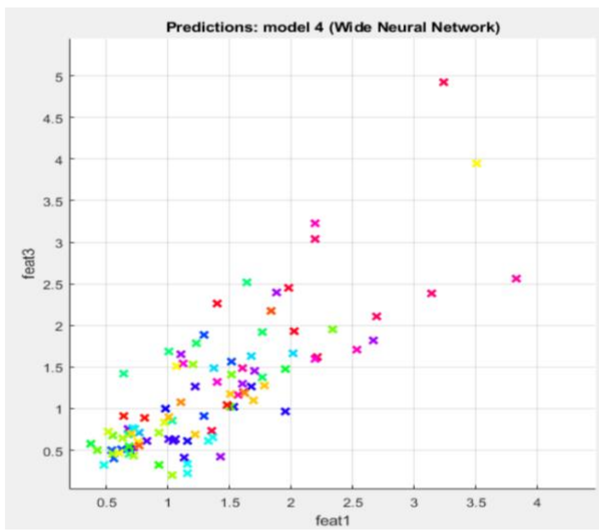

Figure 12: Scatter plot of testing feature (50/50 Cross Validation)

Table 4: Comparison with existing techniques

Method	Dataset	Year	Model	Accuracy
Vanilla CNNs	Oral Cancer Detection	2025	ResNet-101	90.1%
			DenseNet-121	89.5%
Grid search methods	Skin Cancer HAM10000 dataset	2024	Multiples CNN Model	74..23%
State of Art	Melanoma skin cancer detection and classification.	2023	Mobile Net Model	92.7%
			Threshold for segmentation	92.70%
Proposed Approach	Skin cancer ISIC The International Skin Imaging Collaboration	2025	ResNet-65	99.7%

6. Conclusion and future work

This research suggests an automated detection and classification of skin cancer. It also uses basic image processing techniques related to features extraction, segmentation, feature selection and classification. In (Skin cancer ISIC, the International Skin Imaging Collaboration) dataset is a computer vision dataset it should use for detection/recognition tasks. I have considered and enhanced the deep learning model, also design itself. The name of the model is ResNet-65. The model trained then applies the classifier and calculates the accuracy and time. In future, a single CNN learning model and training will be proposed instead of multiple training models. We will create a new CNN learning model and train it entirely from scratch for every single image object detection and classification and more datasets will be taken into account for the experimental procedure and evaluated during statistical analysis.

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Data availability

The data that support the findings of this study are reported at Ref. [9] of this research.

Conflicts of Interest

No conflict of interest is stated by the author.

Authors contributions

Conceptualization: SN, HK; Methodology: SN, MB; Validation: SN, MB; Writing—original draft preparation, SN, HK; Writing—review and editing: SN, MB, HK; Visualization: MB, HK; Supervision: MB, HK; Project administration: MB, HK. The author had approved the final version.

AI usage disclosure

Artificial intelligence tool Grammarly was used only for language polishing and grammatical correction. All scientific and technical contents were created and validated by the authors.

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