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Research Article

Advanced Skin Cancer Detection: A Deep Learning and Transfer Learning Framework for Melanoma Classification

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ABSTRACT

Early identification is essential for successful treatment of skin cancer, a widespread and possibly fatal illness. In recent years, models based on deep learning have shown promise in improving the accuracy of skin cancer detection. This research introduces an innovative method for predicting skin cancer by utilizing Convolutional Neural Networks (CNNs) and employing the DenseNet201 deep learning model for classification. The CNN model is utilized to extract significant features from the images, whilst the DenseNet201 is employed for classification. The proposed CNNs efficiently extracted hierarchical features from the skin images. The low complex structure and convolutional layers helped in identifying nuanced patterns and abnormalities in the input data, making the model effective instruments in detecting cancer at an early stage. The DenseNet201 design is well-known for its densely connected layers, which enable the reuse of features and improve the flow of gradients. The proposed modified DenseNet201 is very efficient in extracting highly useful features from images for the classification of skin cancer. The unique design of its architecture enhances the overall performance efficiency when compared to the existing techniques.

Keywords: Skin cancer, Early detection, Convolutional Neural Networks, DenseNet201.

INTRODUCTION

Skin cancer prediction and classification include the use of sophisticated computer methods to analyze dermatological pictures and evaluate the probability of skin cancer occurrence [1]. This novel methodology entails using sophisticated algorithms and image processing techniques to analyze many attributes of skin lesions, including dimensions, morphology, pigmentation, and surface properties. By using these technologies, healthcare providers may improve the precision and effectiveness of detecting skin cancer in its first phases, enabling prompt intervention and enhancing patient outcomes. This area signifies a notable advancement in using technology to aid in the early identification and classification of skin cancer [2], eventually leading to more efficient and tailored healthcare in the field of dermatology. The prediction and categorization of skin cancer are very important in the field of public health because they help identify the illness early on and ensure proper treatment of this common and possibly fatal condition. Early detection of skin cancer using predictive models enables proactive intervention, leading to substantial improvements in treatment results and reductions in morbidity and death rates [3]. Given the increasing prevalence of skin cancer globally, precise categorization techniques assist healthcare practitioners in differentiating between harmless and cancerous skin abnormalities, hence informing suitable treatment approaches [4]. Moreover, these prognostic techniques assist screening efforts at the population level, allowing for timely detection, tailored therapies, and eventually improving overall rates of survival. The significance of predicting and classifying skin cancer resides in their crucial role in developing preventative healthcare and promoting better patient outcomes [5]. Current methods for predicting and categorizing skin cancer using photos include sophisticated machine learning and computer vision algorithms [6]. These techniques use extensive datasets of dermatoscopic pictures to train algorithms that can accurately identify skin lesions [7]. Feature extraction approaches, such as deep learning architectures like convolutional neural networks (CNNs), are essential for collecting complex patterns and textures that indicate various forms of skin cancer. Moreover, the model incorporates the utilization of image augmentation along with transfer learning approaches to enhance its overall ability to generalize [8]. The current techniques for forecasting and classifying skin cancer using images have made significant advancements, although there are still notable deficiencies in research. Although deep learning approaches have become widespread, there is still a need for enhanced model generalization across various demographics and skin types. Moreover, most current methods mostly concentrate on distinguishing between benign and malignant lesions, disregarding the possibility of more intricate classifications that take into account various subtypes and stages of skin cancer. Moreover, the limited availability of extensive and well-organized datasets is a significant obstacle to the advancement and assessment of reliable models. It is crucial to address these areas of study that need attention in order to improve the precision, dependability, and usefulness of image-based systems for detecting skin cancer. This will eventually lead to more efficient early diagnosis and treatment.

LITERATURE SURVEY

Walaa Gouda et al [9] utilized the methodology of deep learning A Convolutional Neural Network (CNN) is used to classify tumors into two primary categories: malignant and benign. The categorization is accomplished by employing the ISIC2018 dataset. The dataset consists of 3533 skin lesions, including both benign and malignant tumors, as well as nonmelanocytic and melanocytic tumors. The images underwent initial enhancement and refinement using ESRGAN. During the preprocessing stage, the pictures underwent augmentation, normalization, and resizing. Utilizing a Convolutional Neural Network (CNN) approach, skin lesion images may be categorized by aggregating the outcomes gained over several iterations. Subsequently, other transfer learning models, including Resnet50, InceptionV3, and Inception Resnet, were used for the purpose of fine-tuning.

Hardik Nahata et al [10] developed a CNN model with the specific purpose of identifying instances of skin cancer. This model has the capability to classify various manifestations of skin cancer and aid in its prompt detection. The CNN classification model will be built in Python utilizing Keras and TensorFlow as the foundational frameworks. The model is constructed and evaluated using several network topologies, in which the types of layers used for training the network are altered, such as Convolutional layers, Dropout layers, Pooling layers, and Dense layers, among others. The approach will use Transfer Learning techniques to achieve fast convergence.

Mehwish Dildar et al [11] provided an exhaustive and methodical analysis of deep learning methods used to identify skin cancer at an early stage. Analyzed were research articles pertaining to the issue of skin cancer diagnostics that were published in esteemed academic publications. Research results are communicated using many means such as tools, graphs, tables, methodologies, and frameworks to enhance comprehension.

Lisheng Wei et al [12] introduced a refined model for identifying skin cancer that includes feature differentiation via the use of the fine-grained classification approach. The proposed approach comprises two conventional feature extraction modules: a lesion classification network along with a feature discrimination network. The feature extraction module of the recognition model (Lightweight CNN) initially receives two sets of training examples, which include pairs of positive and negative samples. Afterwards, the feature extraction module produces two sets of feature vectors. These vectors are then used to train both the classification networks and feature discrimination networks of the recognition framework at the same time. In addition, a model fusion method is used to improve the performance of the model. This suggested identification strategy efficiently recovers highly discernible lesion characteristics and enhances the model's ability to recognize them, while using a limited number of model parameters. In addition, we have developed a concise semantic segmentation model employing the feature extraction module of the proposed recognition model, the U-Net architecture, as well as a migration training strategy. This model is designed to accurately identify the lesion area in dermoscopy images.

Mohammad Shorfuzzaman et al [13] Proposed a novel transparent design for early detection of melanoma skin cancer using a stacked ensemble of CNNs. The stacking ensemble framework employs transfer learning, where many CNN sub-models, specifically developed for the same classification task, are merged.

Kanchana Sethanan et al [14] created a precise skin cancer classification system (SC-CS) that can accurately distinguish between various types of skin cancer. The particular categories of interest include melanoma, vascular lesions, melanocytic nevus, cutaneous fibromas, benign keratosis, along with various forms of carcinomas as well as skin moles. The system employs image segmentation and CNN methods inside a double artificial multiple intelligence system (AMIS) ensemble model. It leverages optimal results weighting to obtain superior solution quality.

Hsin-Wei Huang et al [15] developed a lightweight, deep learning-based skin cancer classification algorithm that can support primary medical care. The enhanced approach may be used to remote diagnostic apps on mobile devices and cloud platforms. We examined the clinical images and medical records of patients diagnosed with melanoma, seborrheic keratosis, basal cell carcinoma, squamous cell carcinoma, and melanocytic nevus at Kaohsiung Chang Gung Memorial Hospital (KCGMH) between 2006 and 2017. In order to distinguish between benign and malignant skin cancers, we used deep learning techniques that combined multi-class classification with binary classification.

Manoj Kumar et al [16] suggested that an improved method be used for the early identification of three different kinds of skin cancers. The picture of a skin lesion is the input that is being evaluated. The system would classify it as malignant or non-cancerous based on the suggested methodology. Fuzzy C-means clustering is used during the picture segmentation process to identify and divide regions of the image that have similar attributes. Several filters are used to the image during the pre-processing phase to improve its qualities.

PROPOSED METHOD

Skin Cancer Prediction

Within the field of medical progress, the utilization of state-of-the-art technology is crucial in transforming diagnostic methods. An example of a revolutionary advancement is the use of CNNs to forecast skin cancer using picture analysis. Given the rising prevalence of skin cancer globally, it is crucial to promptly and accurately identify it in order to ensure successful therapy. The use of CNNs, a category of advanced machine learning algorithms specifically developed for the purpose of identifying and classifying images, has great potential in improving the precision and effectiveness of skin cancer prediction. This novel method utilizes artificial intelligence to examine complex patterns and characteristics in dermatological photos, resulting in a significant advancement in the early identification and prediction of skin cancer. Ultimately, this contributes to better patient outcomes.

Introduction to Convolutional Neural Networks (CNN)

CNNs are a specific kind of deep neural networks that are specifically engineered to handle and analyze visual input, such as photos and videos. They have shown significant efficacy in tasks like as picture categorization, object identification, and image recognition. Convolutional Neural Networks (CNNs) draw inspiration from the complex organization of the human visual system, replicating the hierarchical arrangement seen in the visual cortex. CNNs are distinguished by their capacity to autonomously and flexibly acquire spatial hierarchies of characteristics from the input data.

Convolutional layers are the essential components of a CNN. These layers use convolutional processes, which consist of applying a tiny, trainable filter (also called a kernel) on the input data by sliding it across. The filter isolates and captures certain local patterns or characteristics, such as edges or textures, from the input. Convolutional layers often use many filters to facilitate the learning of a wide range of intricate and varied characteristics. Convolutional operations play a crucial role in enabling parameter sharing, which in turn reduces the number of parameters in the network and improves computing efficiency.

Pooling layers are a crucial element of CNNs, often positioned after convolutional layers. Pooling is a method of down sampling that decreases the spatial dimensions of the input volume, hence reducing the computational effort and avoiding overfitting. Max pooling, for instance, chooses the highest value among a set of adjacent pixels, preserving the most prominent characteristics.

Convolutional and pooling layers are often placed one after the other until fully linked layers reach the end of the network in a typical CNN architecture. In the context of photo classification, fully linked layers combine the obtained attributes to produce the final result, such as the probabilities of various classes. CNNs use convolutional, pooling, and fully connected layers to acquire hierarchical representations of input data, including both low-level characteristics and high-level concepts.

CNNs has the notable characteristic of translational invariance, which enables them to identify patterns without considering their location inside the input space. This property is essential for jobs using images, since the identification of an item inside a picture should be unaffected by its position.

Datasets

For the Skin cancer prediction, Melanoma Skin Cancer Dataset [17] is used which consists 10,001 images. The aggressive type of skin cancer called melanoma has a high death rate. However, timely identification and treatment may significantly increase the chances of survival. This dataset will be valuable for constructing deep learning models to achieve precise categorization of melanoma. The dataset comprises 9600 photos for training the model and an additional 1000 images for evaluating the model. For the Skin cancer classification, the International Skin Imaging Collaboration (ISIC) dataset [18] is used. The collection comprises 2357 photos depicting both malignant and benign oncological disorders. The total 2,239 images are used for training and 118 images are used for testing purpose.

Proposed CNN

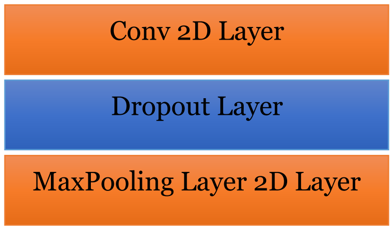

Fig.1 Block A

Block A includes Convolutional 2D layers (Conv2D), Dropout layers, and MaxPooling 2D layers, which are utilized in convolutional neural networks. The Conv2D layer convolves input data with learnable filters to discover key visual patterns and extract features. During training, the Dropout layer randomly discards neuron outputs to provide regularization. This reduces overfitting to increase model generalization. The MaxPooling 2D layer down samples spatially by selecting neighboring pixels' greatest values. This reduces computing load and abstracts input data. Block A layers help convolutional neural networks conduct hierarchical feature extraction, regularization, and down sampling for image processing.

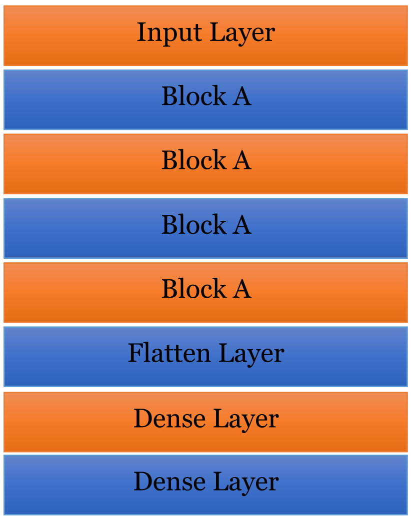

Fig. 2 Proposed CNN Architecture for Skin Cancer Prediction

- Input Layer:

The input layer of a neural network receives external inputs for processing. Its main duty is to accept and prepare input data for network layers. The neural network interfaces with the dataset's raw input characteristics via the input layer. The input layer of a neural network has neurons for each data characteristic or attribute. These receptor neurons provide input feature values to neurons in the next layers without computing. The total amount of neurons in the input layer is determined by the dimensionality of the input data, which corresponds to the number of discrete characteristics.

The input layer contains raw data points like picture pixels or dataset characteristics. These variables are standardized or preprocessed to help the neural network understand data patterns and correlations. Normalization may scale input values to a standard range to improve neural network training convergence and performance. The input layer provides the basis for the neural network's learning process by representing input data that will be modified and altered by succeeding layers. As data passes through the network, the input layer effectively sends pertinent information to the hidden layers, starting neural networks' complex feature extraction and pattern recognition process. In summary, the input layer receives and encodes raw input data to start the neural network's calculation and learning process.

- Convolutional 2D Layer:

The Convolutional 2D Layer, often known as a Conv2D layer, is a crucial component in convolutional neural networks (CNNs), which are extensively used for tasks linked to images. The function of this layer is essential in extracting hierarchical information from input pictures by using convolutional procedures. The Conv2D layer is distinguished by its convolutional kernels or filters. A filter is a small, adaptable matrix that is applied to the input image using convolution to produce a feature map. The convolution procedure entails the multiplication of each element of the filter with corresponding elements of local areas in the input, and then the summing of these products. The outcome is a feature that has undergone convolution, which effectively captures certain patterns or characteristics seen in the input picture.

The concept of weight sharing is a crucial element in the Conv2D layer. A uniform set of filters is used across the whole input picture, enabling the network to acquire knowledge about spatial hierarchies of features. This facilitates the detection of local patterns in the early stages and more intricate, abstract characteristics as the hierarchy becomes more complicated. In addition, Conv2D layers often use activation functions, which are like the Rectified Linear Unit (ReLU), to provide non-linear behavior into the model. The presence of non-linearity is essential for the network to acquire and depict intricate connections within the data. The activation function is applied individually to each element of the output resulting from the convolution procedure.

- Dropout Layer:

Dropout Layer regularization is used in neural network topologies to reduce overfitting and increase model generalization. An overfitted model performs poorly on unseen data because it learns the training data too well, including noise and random oscillations. The Dropout Layer randomly drops out a certain number of neurons during training to avoid any one neuron from becoming unduly dependent on data characteristics or correlations. On each training cycle, the Dropout Layer randomly picks a subset of neurons and zeros their outputs. This stochastically applied approach drops various neurones in each training cycle. Randomness forces the network to acquire stronger characteristics and prevents neurons from specializing to the training data. This helps the network generalize to new cases.

Dropout is usually used during training, not assessment or prediction. All neurons are utilized during testing, but their outputs are scaled by the dropout rate to maintain the predicted result. This allows the model to perform well on fresh data while still benefitting from dropout's regularization impact during training. The dropout rate hyperparameter controls the percentage of neurons lost. Dropout rates typically vary from 0.2 to 0.5. The neural network design and dataset properties determine the dropout rate. The Dropout Layer prevents overfitting, improves model generalization, and strengthens neural network topologies.

- MaxPooling 2D Layer:

Image recognition convolutional neural networks (CNNs) need the MaxPooling 2D layer. Its main goal is to down sample input data spatial dimensions to reduce computational complexity of succeeding layers while keeping key information. This layer spatially down samples two-dimensional picture arrays by picking the greatest value from a group of surrounding values. A kernel or filter, or sliding window, sweeps over input data in predetermined steps in the MaxPooling 2D layer. The maximum window value is kept at each point and the remainder is discarded. This procedure shrinks the input feature map, highlighting important characteristics and removing irrelevant ones. Thus, network parameters are lowered, preventing overfitting and improving computing efficiency.

The MaxPooling 2D layer helps the network achieve translational invariance, making it less sensitive to feature locations in the input data. The layer lets the network detect patterns independent of geographical location by concentrating on important values and rejecting others. This attribute is useful for picture identification jobs when object or feature positions may fluctuate. While MaxPooling is popular, Average Pooling uses the window's average value instead of the maximum. Choice between these strategies relies on task characteristics and network behavior. CNN feature extraction relies on the MaxPooling 2D layer, which helps the network develop hierarchical representations of input data.

- Flatten Layer:

The Flatten layer is essential in neural networks, especially deep learning models. Its main role is to collapse all dimensions save the batch dimension into one dimension to restructure incoming data. This transformation is necessary when switching from multi-dimensional convolutional or recurrent layers to fully connected layers that accept one-dimensional input. The output of a convolutional layer is usually a 3D tensor encoding width, height, and channels. Flattening this 3D tensor into a one-dimensional vector, the Flatten layer connects the convolutional and highly connected layers. Recurrent layers that process data sequences use the Flatten layer to transform their output into a flat vector.

The Flatten layer rearranges the input tensor into a continuous, linear sequence during the forward pass. Reshaping is necessary because thick layers, or completely linked layers, compute using one-dimensional input vectors. In the neural network design, the Flatten layer enables information transmission between layers. Flatten layer implementation does not introduce trainable parameters. Its structural duty is to ensure network layer compatibility. Despite its simplicity, the Flatten layer is crucial to converting spatial or sequential representations to a flattened format suited for fully linked layers. It connects neural network layers, allowing information to flow.

- Dense Layer:

A fully connected layer, or dense layer, is a key building component in neural networks and deep learning models. Each neuron or node in this layer is linked to all neurons in the preceding and following layers, creating a dense network. The adjective "dense" describes the layer's total connectedness. The Dense layer linearly transforms incoming data. The input data are multiplied by weights for each layer neuron and totalled. By passing this summation via an activation function, the model becomes non-linear. The activation function helps the network catch complicated data patterns and correlations that a linear transformation may miss.

The number of neurons in a Dense layer influences the output space's dimensionality and the model's ability to learn complex information. Changing the number of neurons models data abstraction levels. The Dense layer's connection weights are modified using optimization methods like gradient descent during training to reduce the disparity between anticipated output and actual goal. Backpropagation lets the model learn and adapt to training data patterns. The Dense layer functions in feedforward, CNN, and RNN neural network designs. Its simplicity and efficacy make it essential for neural network design and implementation in image classification, natural language processing, and regression.

The above sequence of layers depicts the architecture of a CNN designed for predicting skin cancer using skin pictures. The architecture comprises an initial input layer, followed by many iterations of Block A. Each block integrates a Convolutional 2D Layer to extract features, a Dropout Layer to address overfitting, and a MaxPooling 2D Layer to down sample spatially. The Blocks A are then connected to a Flatten Layer, which transforms the output into a one-dimensional vector. This vector is then inputted into Dense Layers to facilitate the learning of complex patterns. The presence of these completely linked layers enhances the model's capacity to discover intricate linkages within the flattened characteristics. The ultimate Dense Layer generates the output, indicating the probability of skin cancer based on the input photos.

Adam Optimizer

The Adam optimizer is a prevalent optimization technique used in the fields of machine learning and deep learning. It is a modification of the stochastic gradient descent (SGD) algorithm that aims to optimize the weight updates of a neural network in a more efficient manner during the training process. Adam integrates the advantages of two other widely-used optimization approaches, namely RMSprop and momentum. It calculates and keeps track of two types of moving averages for each parameter: the first moment, which represents the mean, and the second moment, which represents the uncentered variance. Subsequently, these moving averages are used to dynamically modify the learning rates for each parameter, enabling the method to achieve quicker convergence and successfully manage gradients with low density. Adam is renowned for its durability, rapid convergence, and capacity to manage objective functions that are noisy or non-stationary. Although widely used, it is crucial to acknowledge that the selection of an optimizer might vary depending on the unique attributes of the issue being addressed. Additionally, fine-tuning hyperparameters, such as the learning rate, may be required to achieve optimum performance.

Skin Cancer Classification

Artificial intelligence has had a tremendous influence on the discipline of dermatology in the sphere of medical diagnostics. The classification of skin cancer has made substantial progress via the use of sophisticated deep learning algorithms. The objective of this study is to employ DenseNet, a CNN architecture recognized for its dense connection patterns, in order to enhance the precision and effectiveness of skin cancer categorization. By using the complex characteristics acquired from numerous layers, DenseNet provides a potent tool for differentiating between different forms of skin cancer, thereby aiding in the early and more accurate detection of the disease.

Modified DenseNet201

DenseNet201 is a convolutional neural network design that is classified under the category of Densely Connected Convolutional Networks (DenseNets). DenseNet201, created by Gao Huang, Zhuang Liu, and Laurens van der Maaten, is a significant improvement in deep learning for tasks involving image identification. The design is distinguished by its intricate connection structure, which distinguishes it from conventional convolutional neural networks.

The main breakthrough of DenseNet201 is its dense block structure, which allows each layer to accept input from all previous layers and share its own feature maps with all subsequent levels inside the block. The high level of interconnectivity in the network facilitates the reuse of features, which in turn enhances the flow of information and the propagation of gradients. Consequently, DenseNet201 demonstrates enhanced parameter efficiency and superior performance in comparison to previous designs.

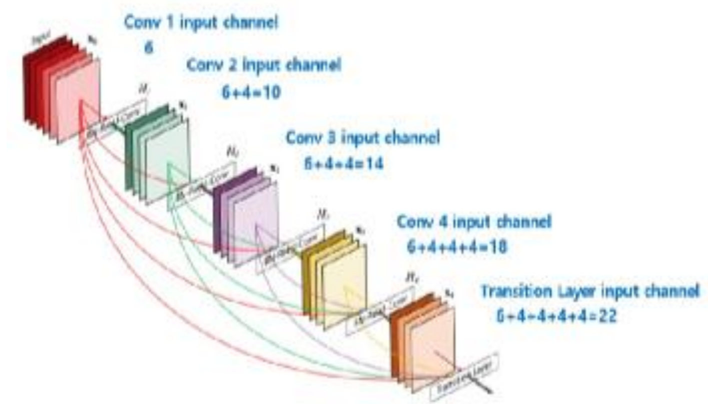

Fig. 3 DenseNet201 Architecture

DenseNet201 is composed of many dense blocks, each including a sequence of convolutional layers with batch normalization and Rectified Linear Unit (ReLU) activations. The tightly linked blocks are interspersed with transition layers that use pooling operations to decrease spatial dimensions and optimize the network's computational performance. The network's output for classification tasks is generally generated by using the final global average pooling layer and one or more fully linked layers.

DenseNet201 is a very sophisticated and robust model that can effectively learn complex hierarchical representations from input data. It consists of 201 layers in the network, making it deep and strong. The model has undergone pretraining on extensive datasets like ImageNet and may be further optimized for diverse computer vision tasks, such as picture classification, object identification, and feature extraction.

The DenseNet201 architecture has been successfully used in several fields, particularly in medical image analysis, because to its exceptional capability to catch complex features and patterns inside pictures, which is of utmost importance in this field. The appeal of BERT in the deep learning field is further enhanced by its success in transfer learning settings, where pretrained models may be fine-tuned for particular tasks using just a little amount of labelled data. In summary, DenseNet201 serves as evidence of the continuous endeavours to create neural network structures that are both efficient and successful in tackling complex image recognition problems.

Proposed Model Architecture

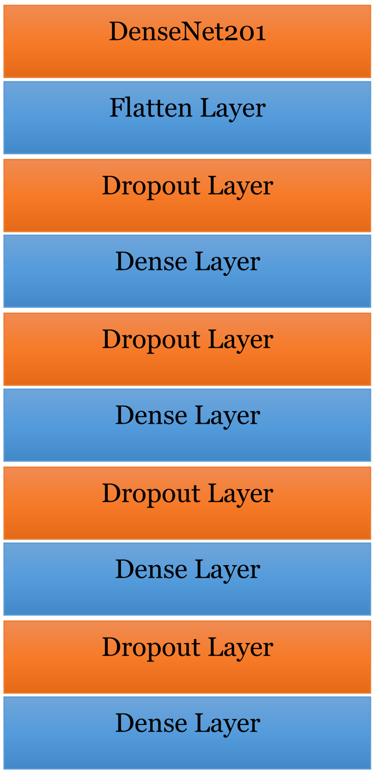

Fig. 4 Proposed model Architecture for Skin Cancer Classification

The proposed model for Skin Cancer Classification has the layers following:

- DenseNet201
- Flatten Layer
- Dropout Layer
- Dense Layer

In the classification of skin cancer using DenseNet201, a highly regarded deep learning structure known for its densely linked convolutional layers, the Flatten layer is used to transform the output of the convolutional layers into a one-dimensional array. Subsequently, a Dropout layer is included to selectively deactivate a portion of neurons, hence mitigating overfitting and improving the overall generalization of the model. Afterwards, a Dense layer is used, which applies a rectified linear unit (ReLU) activation function to add non-linearity and capture intricate patterns in the data. The repetition of Dropout and Dense layers serves the purpose of regularization, which helps to avoid the neural network from excessively depending on certain characteristics. The ultimate Dense layer, often using a SoftMax activation function, generates the probability distribution across several skin cancer classifications, enabling the model to make a classification judgment using the acquired information.

SGD Optimizer

Stochastic Gradient Descent (SGD) is a commonly used optimization technique in the domain of machine learning and deep learning. The main goal of Stochastic Gradient Descent (SGD) is to minimize the cost or loss function linked to a model's predictions by modifying the model parameters. The optimization procedure entails iteratively adjusting the model parameters in a manner that minimizes the loss.SGD fundamentally functions by calculating the gradient of the loss function in relation to the model parameters. The gradient signifies the path of greatest increase of the function, whereas SGD endeavours to go in the opposite direction to obtain the minimum of the loss function. In the context of SGD, the word "stochastic" indicates that it employs a random selection process to choose a subset of training samples (known as a mini-batch) for each iteration, instead of using the full dataset. The use of randomness in this context brings about unpredictability and aids in avoiding local minima.

An important benefit of SGD is its high efficiency, particularly in situations involving large datasets. By using mini-batches, the approach lowers the computational expense linked to calculating gradients on the whole dataset. SGD is highly suitable for training deep neural networks due to its ability to handle large amounts of data, which may be challenging for conventional gradient descent techniques. Although SGD is successful, it does have some limits. The stochastic selection of small batches increases variability, which might result in fluctuations or sluggish convergence. In response to this, many alterations and improvements to the fundamental SGD algorithm have been proposed, leading to the development of distinct variations such as Momentum, RMSprop, and Adam.

The learning rate is a vital hyperparameter in stochastic gradient descent (SGD) that governs the magnitude of the increments made during parameter updates. Choosing an adequate learning rate is crucial for attaining convergence and avoiding issues such as overshooting or sluggish convergence. During training, the learning rate may either be fixed or altered adaptively.

The proposed technique presents an innovative strategy for predicting and classifying skin cancer by using Convolutional Neural Networks (CNNs) and the DenseNet201 architecture. The skin cancer prediction approach utilizes a specifically built Convolutional Neural Network (CNN) that incorporates Conv2D layers to extract features, Dropout layers for regularization, and MaxPooling 2D layers for down sampling. These components work together to provide hierarchical feature extraction. The design comprises an input layer, Conv2D layers, Dropout layers, MaxPooling 2D levels, a Flatten layer, and Dense layers, ultimately resulting in the output of skin cancer probability. In addition, the approach incorporates the Adam optimizer to effectively update the weights during training. The skin cancer classification method employs DenseNet201, which is renowned for its thick connectivity patterns. It also incorporates a Flatten layer, Dropout layer, and Dense layer to improve accuracy. The Stochastic Gradient Descent (SGD) optimizer is used to update parameters, specifically because of its efficiency in dealing with big datasets.

EXPERIMENTAL RESULTS

This section offers a comprehensive analysis of the results received from the simulations carried out following the recommended methodology. The datasets used in the present study was obtained from the open-source website Kaggle [17]. The datasets were processed using the recommended methodologies.

Skin Cancer Prediction

Figure 5 shows the sample images from the dataset.

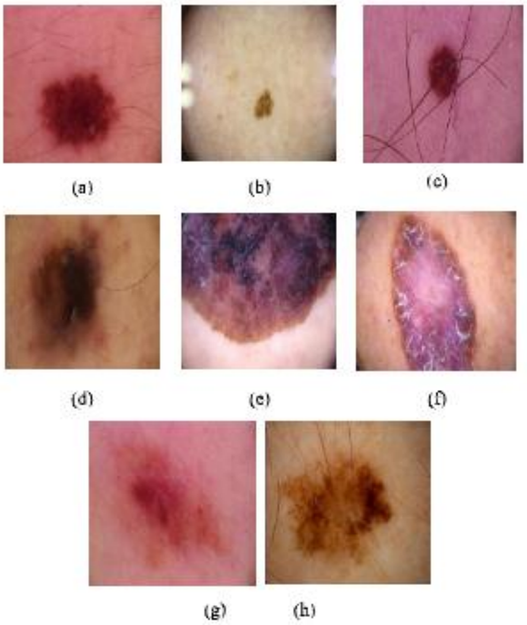

Fig. 5 Sample images from Dataset

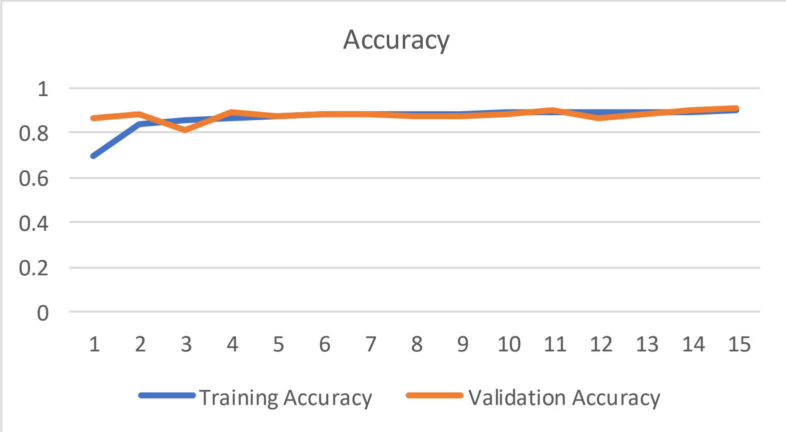

Fig. 6 Training and Validation Accuracy

Training accuracy along with validation accuracy are critical measures for evaluating a machine learning model's efficacy during training. The training accuracy is a metric that indicates how much the model has learnt from the provided data and is defined as the ratio of correctly classified instances in the training dataset. The metric measures the model's ability to predict the labels of the training cases it has seen. A high training accuracy indicates that the model has done a good job of capturing the relationships and patterns seen in the training data. When assessing a model's performance on a dataset that isn't part of its training set, one measure known as validation accuracy is used. The dataset, also known as the validation set, is utilized to independently assess the generalizability of the model. A high validation accuracy proves the model's effective generalization outside of the training set by showing it can make correct predictions on fresh data.

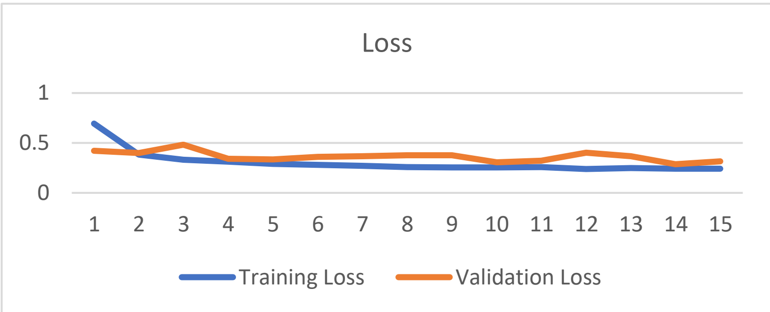

Fig. 7 Training and Validation Loss

In addition to accuracy, training loss along with validation loss are additional measures that assess the model's capacity for learning. The difference between the model's predictions along with the actual labels on the training dataset is measured by the training loss. The main objective of the training phase is to decrease the loss, which means that the model must be trained to provide more accurate predictions. However, even a low training loss does not guarantee good generalization to new and unseen data.

The model's effectiveness on the validation set is evaluated, and the validation loss shows how well the model can generalize. It aids in lowering the issue known as overfitting, which occurs when a model performs badly on fresh, untested data due to its extreme specialization to the training set. Ensuring a harmonious equilibrium between minimizing training loss and validation loss is crucial, as it ensures that the model not only excels in performance on the training data but also effectively transfers its acquired knowledge to novel samples.

Table. 1 Classification Report

	Precision	**Recall**	**F1-Score**
0	0.91	0.91	0.91

1	0.90	0.91	0.90
Total Accuracy: 0.91			

Table 1 indicates a classification report, a commonly used tool in machine learning for evaluating the performance of a classification model. The report often includes metrics like as accuracy, recall, along with F1-score to evaluate the performance of several classes in a classification problem.

Precision is the result of dividing the count of correct positive predictions by the total count of anticipated positives. In the context of binary classification, accuracy is calculated by dividing the number of true positives by the sum of true positives as well as false positives, for each class (0 and 1 in your specific case). A high accuracy implies a minimal occurrence of false positives. Class 0 has a precision of 0.91. When the model predicts Class 0, it has an precision rate of 91%. Class 1 has a precision of 0.90. This indicates that when the model makes a prediction of Class 1, it is accurate 90% of the time.

Recall, often referred to as sensitivity or true positive rate, is the proportion of correct positive predictions to the overall number of real positive instances. The calculation involves dividing the number of true positives by the total of true positives and false negatives. A strong recall implies a minimal occurrence of false negatives. Class 0 has a recall of 0.91. This indicates that the model has a 91% accuracy in properly recognizing instances belonging to Class 0. Class 1 has a recall rate of 0.91. This demonstrates that the model has an accuracy rate of 91% in properly identifying instances belonging to Class 1.

The F1-score is calculated as the reciprocal of the arithmetic mean of the reciprocals of accuracy and recall. It achieves a trade-off between accuracy and recall by considering both false positives and false negatives. Class 0 has an F1-Score of 0.91. This indicates the overall equilibrium between accuracy and completeness in forecasting Class 0. In Class 1, the F1-Score is 0.90. This denotes the comprehensive equilibrium between accuracy and completeness in forecasting Class 1.

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

Table 2 Comparative Analysis

Methods	**Accuracy (%)**
AlexNet [19]	0.86
VGG19 [19]	0.87
GoogleNet [19]	0.87
Xception [20]	0.89
Proposed CNN	0.91

The supplied information in Table 2 provides a comparative comparison of several techniques, highlighting their corresponding levels of accuracy. The assessed techniques include AlexNetachieving an accuracy 0.86, VGG16 achieving an accuracy of 0.87, GoogleNet achieving an accuracy 0.87, Xception achieving an accuracy of 0.89, and a proposed CNN achieving the greatest accuracy of 0.91.

Skin Cancer Classification

The collection comprises 2357 photos depicting both malignant and benign oncological disorders, sourced from The International Skin Imaging Collaboration (ISIC). The photos were categorized according on the ISIC classification, and all subgroups were evenly distributed, except for melanomas and moles, which had a somewhat higher number of images.

The dataset includes the following diseases:

- Actinic keratosis
- Basal cell carcinoma
- Dermatofibroma
- Melanoma

- Nevus
- Pigmented benign keratosis – seborrheic keratosis
- Squamous cell carcinoma
- Vascular lesion

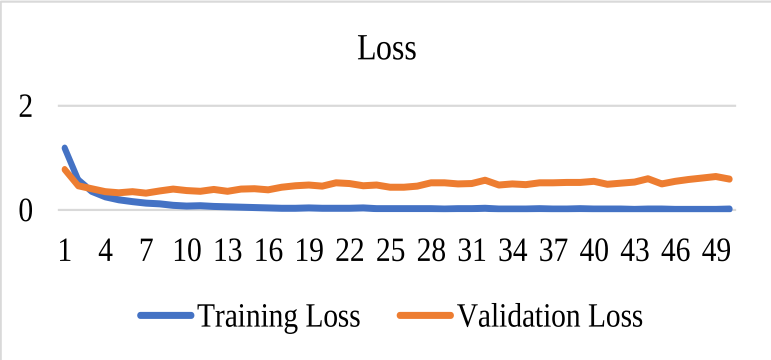

Fig. 8 Training and Validation Loss

The given data displays in figure 8 shows the loss values for training and validation of a neural network over a span of 50 epochs. The training loss, which measures the discrepancy between the predicted and actual values on the training dataset, consistently falls from an initial value of 1.1920 to a substantially lower value of 0.0192 by the 50th epoch, demonstrating the model's enhanced capacity to accurately represent the training data. Simultaneously, the validation loss, which quantifies the performance on a distinct validation dataset, shows a same declining pattern, although with intermittent variations. The validation loss achieves its minimum value of 0.3238 in the 7th epoch but exhibits marginal increments in subsequent epochs.

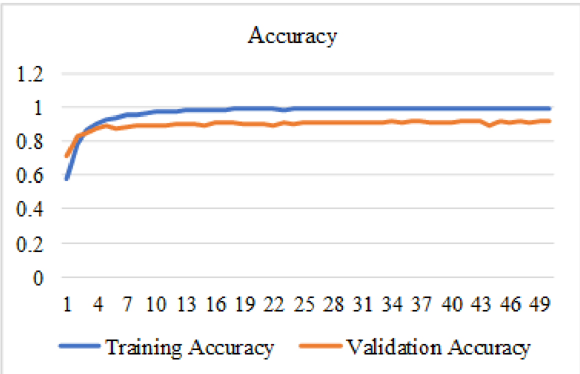

Fig. 9 Training and Validation Accuracy

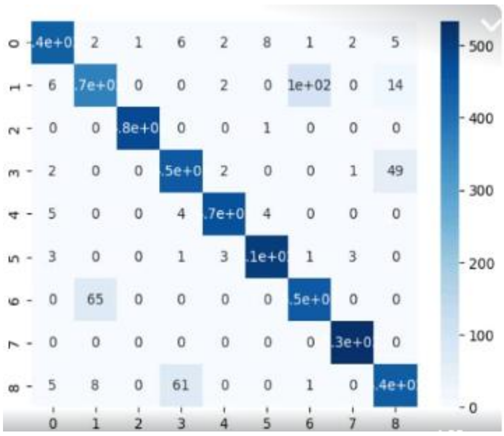

Fig.10 Confusion Matrix

A confusion matrix is a pivotal instrument in the domain of machine learning and statistics used to evaluate the efficacy of a classification model. The breakdown of a model's predictions into four categories, namely true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), offers a thorough and complete assessment of its performance. The models' predictions are compared to the dataset's actual labels to identify the categories.

A confusion matrix is a matrix where the rows correspond to the true classes or labels, and the columns correspond to the anticipated classes made by the model. The primary diagonal of the matrix relates to the accurate predictions (true positives and true negatives), whereas the non-diagonal entries indicate the mistakes produced by the model (false positives and false negatives). This configuration enables a distinct representation and comprehension of the dispersion of forecasts across several categories.

Each of the four components of the confusion matrix has distinct meanings. True positives refer to cases where the model accurately predicts the positive class, whereas true negatives are examples properly identified as the negative class. False positives occur when instances are inaccurately projected as positive, while false negatives occur when instances are inaccurately forecasted as negative. These factors are essential for computing diverse performance measures, like as accuracy, precision, recall, and F1 score, which provide insights into distinct aspects of the model's efficacy.

Table. 3 Performance Report

Metric	**Value**
Precision	0.9186
Recall	0.9179
F1-Score	0.9178
Kappa Score	0.9080
Accuracy	91.8%

The Performance Report is shown in Table 3. The precision, which measures the accuracy of positive predictions, is given as 0.9186, suggesting a high percentage of correctly identified positive cases. The recall, which measures the capacity to accurately detect all relevant occurrences, is recorded as 0.9179, indicating a robust ability to recognize true positives. The F1-Score, a composite measure that incorporates both accuracy and recall, is given as 0.9178, suggesting a well-balanced performance in terms of precision and recall. Furthermore, the Kappa Score, which measures the amount of agreement amongst raters above what would be expected by chance, is documented as 0.9080, indicating a strong agreement between the model's predictions and the actual results.

Table. 4 Comparative Analysis

Method	**Accuracy (%)**
Resnet50 [21]	42.66
CNN [22]	88.89
Modified Densenet201	91.82

The provided information in Table 4 presents a comparative examination of several techniques used for picture classification, with a specific emphasis on their individual accuracies. The techniques encompass Resnet50, CNN (Convolutional Neural Network), and Densenet201. The accuracy figures are reported for each approach, with Resnet50 obtaining an accuracy of 42.66%, CNN exhibiting a far better accuracy at 88.89%, and Modified Densenet201 surpassing both with an accuracy of 91.82%.

CONCLUSION

Significant advancements in cancer diagnosis and dermatology may be made possible by deep learning, as demonstrated by the experimental analysis. In this study, we investigated the application of deep learning models in the prediction and classification of skin cancer. The proposed CNN model obtained an accuracy of 91% in predicting the presence of skin cancer and the proposed modified DenseNet201 model obtained an accuracy of 91.82%. The accuracy scores attained by both the modified DenseNet201 and the suggested CNN models indicate a significant progress in the early identification of skin cancer. These solutions possess the capability to aid dermatologists and healthcare professionals in making more precise and prompt selections, ultimately resulting in enhanced patient outcomes.

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