INTELLIGENT DIAGNOSIS SYSTEM FOR SKIN CANCER DETECTION AND CLASSIFICATION USING DEEP LEARNING

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Department of Electronics Engineering

CERTIFICATE

This is to certify that the Thesis on **"Intelligent Diagnosis System for Skin Cancer Detection and Classification using Deep Learning"** is a bonafide work of Harsh Choubey, Siddhant Jain, submitted to the Rashtrasant Tukadoji Maharaj Nagpur University, Nagpur in partial fulfillment of the award of a Bachelor of Engineering , in Electronics has been carried out at the Department of Electronics Engineering, Shri Ramdeobaba College of Engineering and Management, Nagpur during the academic year 2022-23.

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DECLARATION

I, hereby declare that the thesis titled **"Intelligent Diagnosis System for Skin Cancer Detection and Classification using Deep Learning"** submitted herein, has been carried out in the Department of Electronics Engineering of Shri Ramdeobaba College of Engineering & Management, Nagpur. The work is original and has not been submitted earlier as a whole or part for the award of any degree / diploma at this or any other institution / University.

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PROJECTEES

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ABSTRACT

The incidence of skin cancer, including melanoma, is on the rise worldwide, leading to increased morbidity and mortality rates. Early and accurate detection and classification of skin cancer can significantly improve patient outcomes. There is a higher probability that some people may develop skin cancer at some point in their lives since the population will continue to expand in the upcoming years. This indicates that identifying skin cancer images is a major scientific concern. Traditional approaches to the examination of skin cancer images, however, yielded less accurate outcomes than more modern approaches. If found early, certain skin cancers can be successfully diagnosed.

Our system leverages the power of deep learning algorithms, specifically convolutional neural networks (CNNs), to analyze skin images and automatically detect and classify skin lesions as benign or malignant. The system is trained on a large dataset of skin images with annotated labels, including images of various skin lesion types, such as melanoma, basal cell carcinoma, squamous cell carcinoma, and benign lesions. We presented a deep learning-based classification approach for skin cancer image classification in this paper. The dataset HAM10000 was used as input for the model, which was created in Python using machine learning algorithms. We proposed three models for accuracy comparison, and in model-2 we got promising results.

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Skin cancer is one of the most dangerous forms of cancer. It occurs when the skin is exposed to excessive sunlight, which causes the abnormal proliferation of skin cancer. Because skin cancer tends to spread gradually to other body regions and is more treatable in the early stages, early detection is ideal[1]. Melanoma is the most dangerous type of skin cancer and is one of the cancers with the highest mortality rate. Family history, primary melanoma, numerous clinically unusual oles or dysplastic nevi[2][3], inherited genetic mutations, sun exposure[4], and several clinically atypical moles or dysplastic nevi are risk factors for melanoma. Signs of melanoma include a sizeable area of brown with darker speckles, a mole that bleeds, varies in size, texture, or color, a little lesion that has an erratic border with spots that are red, pink, white, blue, or blue-black burning, or itching sore that hurts. Dark lesions on the mucous membranes lining your mouth, nose, vagina, or anus, as well as on your palms, soles of your feet, fingers, or toes.

Early detection of skin cancer is crucial because it allows for timely intervention and treatment, increasing the chances of successful outcomes. Skin cancer, particularly melanoma, can spread to other body parts if left untreated, making it more difficult to treat and potentially resulting in higher morbidity and mortality rates. Early detection through regular skin self-examination, awareness of risk factors, and timely medical evaluation can lead to prompt intervention and better prognosis for individuals at risk of skin cancer.

1.2 Objectives of the Project

The objective of the "Intelligent Diagnosis System for Skin Cancer Detection and Classification using Deep Learning" project is to develop a sophisticated and accurate system that can assist in the early detection and classification of skin cancer using deep learning techniques. Skin cancer is a prevalent form of cancer that can be deadly if not diagnosed and treated promptly. Early detection plays a crucial role in improving patient outcomes, as it allows for timely intervention and treatment. The proposed system aims to leverage the power of deep learning, a subset of machine learning, to automatically analyze skin lesion images and accurately classify them as benign or malignant. Deep learning algorithms, such as Convolutional Neural Networks (CNNs), have shown remarkable success in various image recognition tasks, including medical image analysis.

By utilizing deep learning techniques, the system aims to achieve high accuracy and sensitivity in detecting and classifying skin cancer lesions. The system will utilize a large dataset of skin lesion images, including both benign and malignant lesions, to train and fine-tune the deep learning model. The dataset will be carefully curated and annotated by dermatologists to ensure the accuracy and reliability of the system. Various data preprocessing techniques, such as image normalization, resizing, and augmentation, will be employed to enhance the performance and robustness of the model.

Once the model is trained, the system will be able to automatically analyze skin lesion images and provide real-time predictions on whether the lesion is benign or malignant. The system will also provide additional information, such as the probability score of the classification, to assist dermatologists in making informed decisions. The system will be designed with a user-friendly interface, allowing dermatologists to easily upload and analyze skin lesion images, view the results, and make appropriate clinical decisions. The performance of the system will be evaluated using rigorous validation methods, including cross-validation and comparison with ground truth diagnoses made by dermatologists. The goal is to achieve high accuracy, sensitivity, and specificity in the detection and classification of skin cancer lesions. The system will be iteratively refined and optimized based on feedback from dermatologists and performance evaluation results. The ultimate objective of the project is to develop a reliable and accurate intelligent diagnosis system that can aid dermatologists in early detection and classification of skin cancer lesions. By providing timely and accurate information, the system has the potential to improve patient outcomes, reduce unnecessary biopsies, and contribute to more effective skin cancer management strategies. The project aims to advance the field of dermatology by harnessing the power of deep learning and creating a valuable tool for dermatologists in their clinical practice.

1.3 Generalized block diagram with explanation

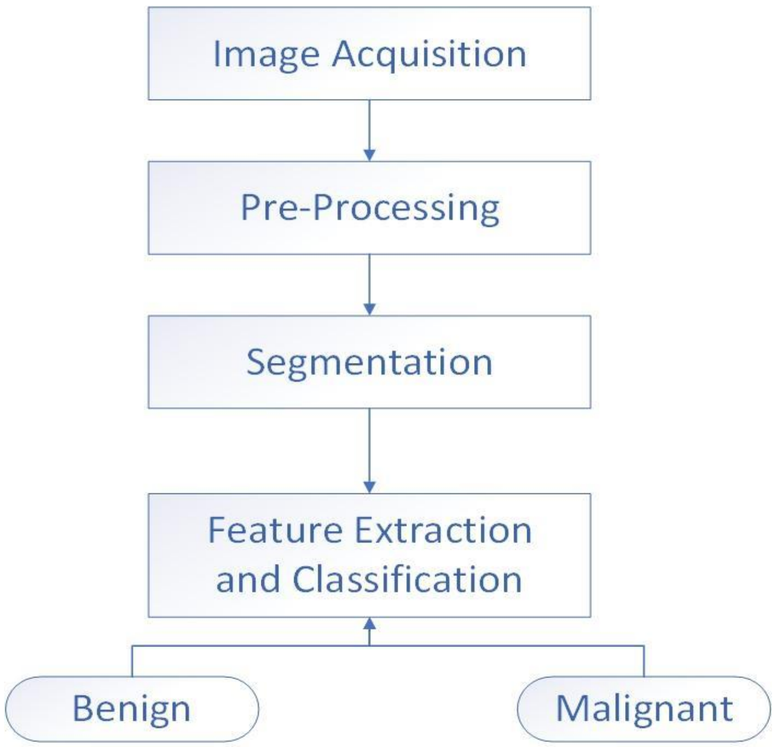

Figure 1. Block diagram of Skin Cancer Detection

1.3.1 Image Acquisition

Figure 1. is the generalized block diagram of the flow of the project. Image acquisition is the first step in the intelligent diagnosis system for skin cancer detection and classification using deep learning. It involves capturing high-quality images of the skin lesions or moles that are suspected to be cancerous. There are various methods of image acquisition used in this system, including dermoscopy, clinical photography, and digital imaging.

Dermoscopy is a non-invasive imaging technique that involves using a dermatoscope, a handheld device with magnifying lenses and a light source, to capture images of the skin lesions. Dermoscopic images provide detailed information about the surface and subsurface structures of the lesions, such as pigment patterns, blood vessels, and other features that are not visible to the naked eye. These images are crucial for accurate diagnosis and classification of skin lesions.

Clinical photography involves capturing high-resolution images of the skin lesions using a digital camera. The images are taken from different angles and distances to capture the lesion's size, shape, color, and texture accurately. Clinical photographs are widely used in telemedicine and remote diagnosis, where dermatologists can review the images and provide a diagnosis without the need for an in-person consultation.

Digital imaging involves using specialized imaging equipment, such as multispectral imaging or confocal microscopy, to capture images of the skin lesions at various depths and wavelengths. These images provide detailed information about the cellular structures and characteristics of the lesions, which can aid in accurate diagnosis and classification.

The acquired images are then used as input data for the deep learning algorithms in the intelligent diagnosis system. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are trained on large datasets of labeled skin lesion images to learn patterns and features associated with different types of skin cancer. These models can then classify the lesions as benign or malignant with high accuracy based on the learned patterns.

1.3.2 Pre-Processing

The pre-processing step is a critical stage in developing an intelligent diagnosis system for skin cancer detection and classification using deep learning. It involves several techniques to prepare the raw skin image data for further analysis and classification by the deep learning model.

Firstly, image acquisition and normalization are performed. Images of skin lesions are acquired from various sources such as dermoscopes or digital cameras. These images may have variations in terms of resolution, illumination, and color. Therefore, normalization techniques such as resizing, cropping, and color correction are applied to ensure consistency and standardization across the dataset.

Next, image augmentation techniques are employed to artificially increase the diversity and size of the dataset. These techniques include rotation, scaling, flipping, and adding noise to the images, which help in improving the model's ability to generalize and recognize skin lesions with different orientations, sizes, and textures.

Further, image enhancement techniques are applied to improve the quality and visibility of skin lesions. This may involve contrast enhancement, histogram equalization, and filtering to enhance the features of interest and reduce noise. Additionally, the pre-processing step includes data splitting, where the dataset is divided into training, validation, and testing sets. The training set is used to train the deep learning model, the validation set is used for hyperparameter tuning and model selection, and the testing set is used to evaluate the final model's performance.

Lastly, data normalization is performed to standardize the pixel intensity values of the images. Common normalization techniques include min-max scaling or z-score normalization, which help in reducing the impact of differences in pixel intensity values across images.

1.3.3 Segmentation

The segmentation step in an intelligent diagnosis system for skin cancer detection and classification using deep learning is a crucial process that involves identifying and isolating the regions of interest (ROIs) in skin images. It aims to separate the suspicious areas of the skin from the healthy areas, which aids in accurate detection and classification of skin cancer.

During the segmentation step, the CNN processes the input skin image and generates a binary mask that highlights the regions suspected to be cancerous. This binary mask is then used to segment and extract the ROIs from the original skin image. The segmentation process can be performed at different levels of granularity, ranging from pixel-level segmentation to region-level segmentation, depending on the desired level of detail.

The segmented ROIs are further processed and analyzed in subsequent steps of the skin cancer detection and classification system, such as feature extraction and classification, to determine the type and severity of skin cancer. Accurate segmentation of the ROIs is critical for precise identification and characterization of skin lesions, as it helps in reducing false positives and false negatives, and improves the overall diagnostic accuracy of the system.

1.3.4 Feature Extraction and Classification

The feature extraction and classification steps are crucial components of an intelligent diagnosis system for skin cancer detection and classification using deep learning. In the feature extraction step, relevant features or patterns are extracted from the input skin lesion images to represent the characteristics of the skin lesions. Deep learning techniques such as convolutional neural networks (CNNs) are commonly used for this task as they are capable of automatically learning discriminative features from large datasets.

During the feature extraction step, the input images are processed through multiple layers of convolutional and pooling operations to capture local patterns and spatial information. These convolutional layers are designed to automatically learn meaningful features such as edges, textures, and shapes that are relevant to skin cancer classification. The pooling layers help in reducing the spatial dimensions while preserving important features.

Once the features are extracted, they are fed into the classification step where a classification model is trained to categorize the skin lesions into different classes such as benign or malignant. This step involves using machine learning algorithms, such as support vector machines (SVMs) or softmax classifiers, to make predictions based on the extracted features. The classification model is trained on a labeled dataset of skin lesion images with known diagnoses to learn the relationships between the features and the corresponding classes.

The performance of the classification model is evaluated using various metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve. The model is fine-tuned iteratively to improve its accuracy and generalization capability.

CHAPTER 2

LITERATURE REVIEW

The present study seeks to expound on the melanoma detection findings for prediction, which were obtained through multiple analyses on diverse datasets and various data mining techniques, thereby producing results that closely approximate the true values. Specifically, this research provides a comprehensive review and analysis of numerous investigations, a meticulous literature assessment of the current algorithms for skin cancer diagnosis, and an accurate comparison of their respective merits.

Ding et al. [5] proposed a lightweight recognition model based on the fine-grained classification concept. The model comprises two frequent feature extraction modules, namely, the lesion classification network and the feature discrimination network. These modules receive two sets of training samples as input, and their outputs are utilized to train the model's two classification and feature discrimination networks. The study used Lightweight R-CNN, which indicated that MobileNetV1 and DenseNet-121 are more noteworthy and superior in several evaluation indicators, making them ideal as lightweight feature extractors for dermoscopy image lesion identification models, with an accuracy of 86.5% and 83.7%, respectively.

In their study, Ashraf et al. [6] trained the system exclusively on images containing melanoma cells and utilized an ROI (Region of Interest) model to discover discriminative features. A Convolutional Neural Network (CNN)-based transfer learning model with data augmentation was employed for ROI pictures of the DermIS and DermQuest datasets. The model uses the K-means approach to extract features. The accuracy rates for DermIS and DermQuest provided by the proposed system were 97.9% and 97.4%, respectively.

Adegun et al. [7] have introduced a unique system for the automatic diagnosis of skin cancer, which utilizes an encoder-decoder Fully Convolutional Network (FCN) in the first stage of their proposed structure. Their system comprises two phases, and a novel FCN-Dense Net Framework is employed in the second stage. The architecture is constructed by connecting the dense components using a transition layer and concatenation approach. Despite having limited data, the entire approach works exceptionally well. When tested on the HAM10000 dataset, which contains over 10,000 images representing seven different disorders, the suggested model achieved scores of 98 percent accuracy, 98.5 percent recall, and 99 percent AUC.

Similarly, A. Naeem et al. [8] have presented a systematic literature review of the most recent research on melanoma classification using Convolutional Neural Network

(CNN). In this study, CNN classifiers were discussed, and their accuracies were compared when tested on non-published datasets. The primary aim of this research was to gather state-of-the-art research that identifies recent trends and new challenges for melanoma diagnosis and investigates existing solutions for melanoma detection using deep learning. Consequently, this study can be useful for researchers working in the domain of melanoma detection. The authors employed various CNN architectures like AlexNet, VGG22Net, DCNN, and FCNN, and the CNN architecture with transfer learning achieved the highest accuracy of 98.6%.

The deployment of deep neural networks is a crucial process that relies heavily on the appropriate manual selection of the neural architecture. However, this process is often time-consuming and can impede progress in the field. To address this challenge, A. Kwasigroch et al. [9] have proposed a group of methods called neural architecture search (NAS) to tackle the medical task of malignant melanoma detection. The effectiveness of this approach has been demonstrated through practical applications, which has led to increased accuracy. Specifically, the hill-climbing search strategy was employed alongside network morphism operations to explore the search space. In this study, five different networks (Network A, B, C, D, E, and F) were used to assess the accuracy of the model. Network F, with a 75.75% accuracy rate, outperformed the other four networks in terms of accuracy.

In a related development, Andre Esteva et al. [10] proposed a single convolutional neural network (CNN) model that is trained end to end from images using only pixels and illness labels as inputs. The algorithm utilized 129,450 clinical photos from the dataset and leveraged a GoogleNet Inception v3 CNN architecture [11] that was transfer-learned after being pre-trained on over 12.8 million photos from the 2014 ImageNet Large Scale Visual Recognition Challenge [12]. The author proposed two methods to validate the effectiveness of the algorithm. Firstly, a three-class disease partition was used, achieving an accuracy of 72.1 ± 0.9%. Secondly, the model was tested using a nine-fold cross-validation technique, which yielded an overall accuracy of 55.4 ± 1.7%. The usefulness of the partitioning approach was demonstrated by the fact that a CNN trained on a finer disease partition outperforms one trained directly on three or nine classes.

DNi Zhang et al. [13] proposed a novel optimized technique for the diagnosis of skin cancer from input images. The approach relies on the Convolutional Neural Network (CNN) architecture, and an improved version of the Whale Optimization Algorithm is employed to optimize the CNN's efficiency. The optimization algorithm is utilized to achieve an optimal selection of weights and biases in the network, leading to the minimization of the network output error and the desired output. The performance of the suggested technique is evaluated using Dreamquest and DermIS benchmarks, and the results are compared to those obtained from ten other methods, such as the semi-supervised method, Spot-mole tool, AlexNet, Ordinary CNN, VGG-16, LIN, Inception-v3, and ResNet. The performance indices used for evaluation include specificity, accuracy, sensitivity, NPV, and PPV.

CHAPTER 3

PROPOSED METHOD

The proposed method for skin cancer detection using deep learning involves a three-step process: data collection, model development, and testing. In the first step, a large dataset of skin images is collected, including both healthy skin and skin with different types of cancer. The dataset is then preprocessed to remove any noise and to normalize the images for use in the model.

In the second step, a deep learning model is developed to detect skin cancer from the preprocessed images. The model uses convolutional neural networks (CNNs) to extract features from the images and a fully connected layer to classify the images into different types of skin cancer. The model is trained using a large number of images with known labels.

In the final step, the model is tested on a separate dataset of skin images to evaluate its accuracy in detecting skin cancer. The testing dataset includes both healthy skin and skin with different types of cancer**.**

The next stage in the project involves the development of three separate deep learning models, with the purpose of conducting a comprehensive comparative analysis. The ultimate goal is to identify the most optimal performing model among the three, which will then be selected as the primary model for skin cancer detection in the subsequent stages of the research. This meticulous approach ensures that the chosen model is thoroughly evaluated and chosen based on its superior performance, paving the way for more accurate and reliable skin cancer detection techniques.

3.1 Dataset Preparation

The HAM10000 dataset is a reliable resource for training artificial neural networks to automatically identify pigments of skin diseases in dermoscopy images. This dataset comprises 10,015 dermatoscopic images that were collected over a 20-year period from the Department of Dermatology at the Medical University of Vienna in Austria and Cliff Rosendahl's Skin Cancer Practice in Queensland, Australia[14]. The images in the dataset represent multiple chromatic lesions and are collected from diverse populations, particularly from individuals with a propensity for melanoma and nevi skin diseases.

The HAM10000 dataset includes images from seven different diagnosis subgroups, which are based on the type of skin cancer. These seven classes of skin lesions are Basal Cell Carcinoma (Bcc), Benign Keratosis (Bkl), Melanocytic Nevi (Nevi), Dermatofibroma (Df), Melanoma (Mel), Vascular Lesions (Vasc), and Actinic Keratoses (Akiec). Each class represents a specific type of skin lesion that may require accurate and early detection for proper diagnosis and treatment. The HAM10000 dataset is a valuable resource for developing an intelligent diagnosis system for skin cancer detection and classification using deep learning techniques. The large number of images in the dataset allows for training and evaluating deep learning models with a substantial amount of data, which can lead to more accurate and robust results. The diverse nature of the images, collected from different populations and including various types of skin lesions, makes the dataset suitable for training models that can generalize well to different skin types and lesion types.

The dataset's quality is ensured by the reputable sources from which the images were collected, including the Department of Dermatology at the Medical University of Vienna and Cliff Rosendahl's Skin Cancer Practice. These sources have extensive experience and expertise in diagnosing and treating skin diseases, which adds to the reliability of the dataset. Moreover, the long period of data collection over 20 years adds temporal diversity to the dataset, which can be beneficial for developing models that are robust to changes in skin lesion characteristics over time.

By utilizing the HAM10000 dataset in the exploratory data analysis (EDA) step, researchers can gain insights into the characteristics and patterns of the data, preprocess and transform the images, visualize and analyze the data statistically, and benchmark different models to build an effective and reliable skin cancer diagnosis system.

3.2 Data Pre-processing

The dataset used for this study consisted of 10,015 dermatoscopic images, each with a size of 100 x 100 x 3 pixels. These images were initially classified into 7 different classes. However, one issue with the dataset was that there was an imbalance in the distribution of images among the classes. Specifically, the class for melanocytic nevi had approximately 6,900 images, which was significantly higher than the number of images in the other classes.

To address this issue of uneven data distribution, the dataset was manipulated by adding new images. This was done by rotating and flipping the original images, resulting in an increase in the overall dimension of the dataset as shown in Figure 2. As a result, the total number of images in the dataset increased to 14,915 after manipulation.

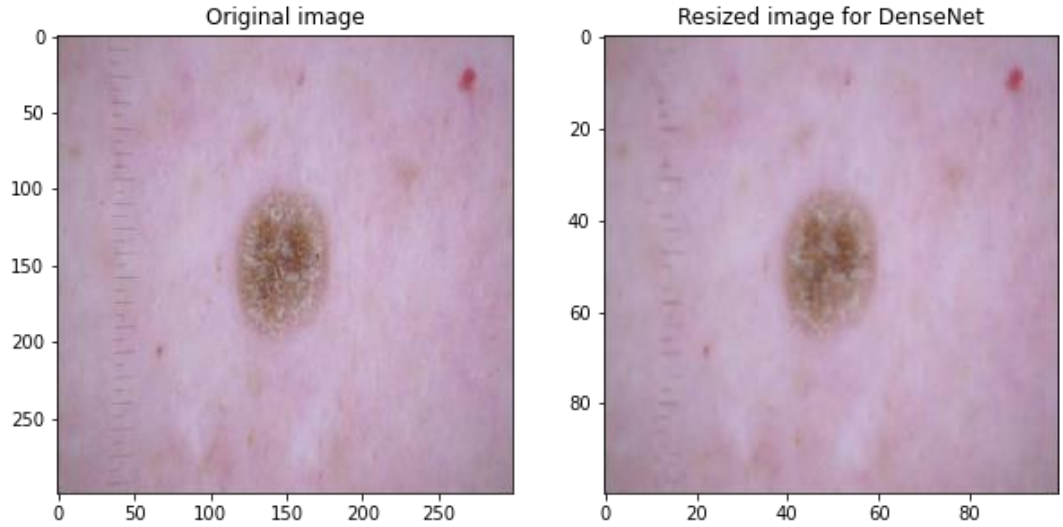

Figure 2. Resized input image after data manipulation

The purpose of this manipulation was to overcome the problem of overfitting, which can occur when a machine learning model is trained on imbalanced data. Overfitting is a phenomenon where a model learns to perform well on the training data but fails to generalize to new, unseen data. By increasing the number of images in the dataset and balancing the distribution of images across the classes, the researchers aimed to improve the generalization performance of the model.

After the dataset manipulation, the final dataset was split into training and testing datasets. Specifically, 20% of the images were set aside for testing, while the remaining 80% were used to train the model. This split is a common practice in machine learning to evaluate the performance of the model on unseen data.

The dataset used in this study initially had an issue of uneven data distribution, with one class having significantly more images than the others. To address this issue, new images were added to the dataset by rotating and flipping the original images. This increased the overall dimension of the dataset and helped to balance the distribution of images across the classes. The final dataset was then split into training and testing datasets for model evaluation.

3.3 Data Augmentation

In order to tackle the problem of overfitting in a single class, data augmentation techniques were employed in this study. Specifically, to ensure that the dataset is evenly distributed, multiple copies of the remaining six classes were developed through data augmentation. The data augmentation process involved rotating the images by 90 degrees clockwise and counter-clockwise. Figure 3 shows the result after augmenting and manipulating input images. This helped to create variations in the orientation of the images, making the dataset more diverse and robust. Additionally, the images were flipped by 180 degrees, further increasing the diversity in the dataset. These augmented images were then mixed with the original images, creating a larger and more diverse dataset for training the model.

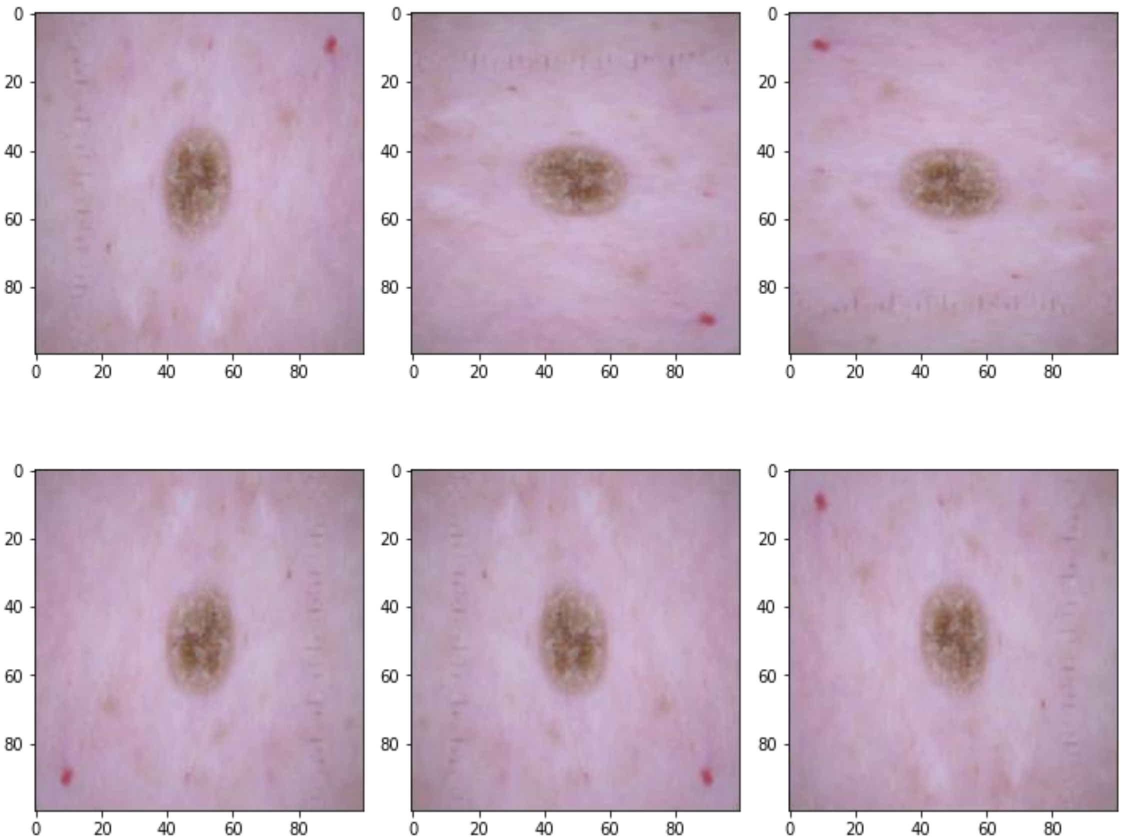

Figure 3. Rotated and Flipped Image for balanced dataset

It's worth mentioning that data augmentation was only applied to the training dataset in order to maintain the objectivity of the model. The testing dataset, on the other hand, was left unaltered, except for resizing the images to a standardized scale between 0 and 1. This ensured that the testing dataset remained unbiased and representative of real-world scenarios. Data augmentation is a common technique used in machine learning to increase the diversity of the training dataset without collecting new data. By introducing variations in the images, data augmentation helps to expose the model to different scenarios and improves its ability to generalize to unseen data. This can be particularly useful in cases where the dataset is limited or imbalanced, as it helps to address the issue of overfitting and improves the model's performance.

The use of data augmentation in this study aimed to address the uneven distribution of images across different classes in the dataset. By creating augmented copies of the other six classes, the researchers were able to balance the dataset and reduce the risk of overfitting in a single class, such as melanocytic nevi. This approach helped to create a more robust and diverse dataset for training the model, enabling it to learn from a wider range of image variations and improving its ability to classify dermatoscopic images accurately.

3.4 Ensemble Models

The next step in the project involves the development of deep learning models. Three models are created for comparative analysis, with the goal of identifying the best-performing model to be used as the primary model. The first model serves as the baseline and utilizes three convolutional layers with subsequent max pooling after each convolution operation. The flattened layer is then applied, which converts the two-dimensional feature maps obtained from the convolutional layers into a one-dimensional vector, allowing compatibility with fully connected layers for prediction purposes, as fully connected layers require one-dimensional inputs. The total number of trainable parameters in the model is 2,124,839. After training, the model achieved a training accuracy of 79.85%, testing accuracy of 76.54%, and validation accuracy of 77.48%. However, the model encountered challenges with low accuracy in both testing and validation phases. Further improvements and optimizations may be needed to enhance the model's performance in these areas.

The second model, referred to as Sequential Model 1, has been designed to overcome the issues of inaccuracy and overfitting observed in the baseline model. Notably, this model includes an increased number of convolutional layers, totaling four, and introduces batch normalization after each convolutional block. Batch normalization is a well-known technique in deep neural networks that enhances training stability and accelerates convergence by normalizing the inputs through scaling and shifting during training. The mathematical expression for batch normalization is as follows:

Given a mini-batch of input data X = {x_1, x_2, ..., x_m}, where m represents the batch size, the batch normalization operation can be defined as:

$$z(i) = \frac{(x(i) - \mu(B))}{\sqrt{\sigma(B^2)} \times \gamma + \beta}$$

Equation (3.1). Batch Normalization

where,

z(i) = Normalized output

x(i) = Input to the i-th neuron in the batch

μ(B) = Batch Mean

$\sigma(B)^2$ = Batch Variance

ε = Small constant added for numerical stability

γ = Scaling factor

β = Shifting factor.

Batch normalization mitigates internal covariate shift, improves generalization performance, and allows for higher learning rates, thereby accelerating the training process. Sequential Model 1 consists of a total of 182,663 trainable parameters. After training, the model achieved a training accuracy of 92.56%, testing accuracy of 92.12%, and validation accuracy of 92.3%. Notably, this model demonstrated significant parameter reduction while also improving accuracy compared to the baseline model.

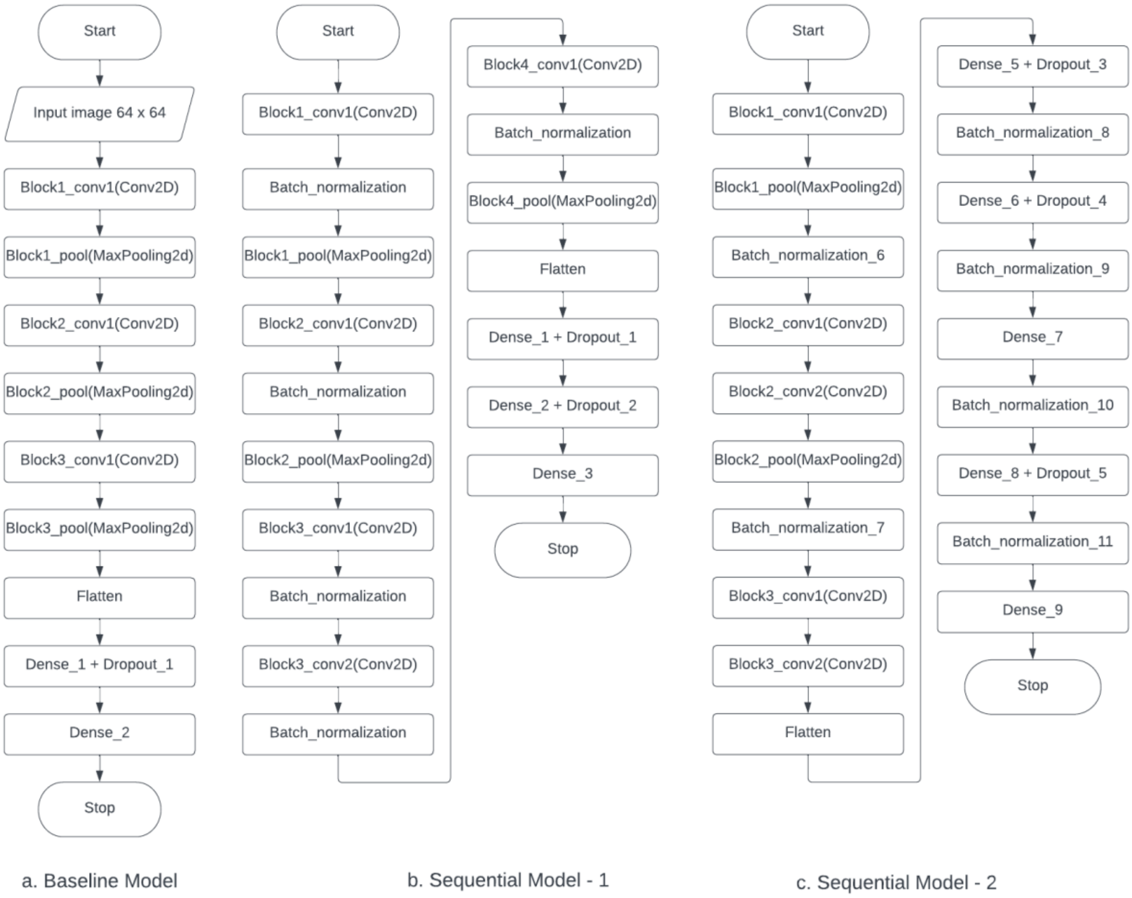

Figure 4. Flow diagram of three convolution models

Figure 4 shows the flow of all the three ensemble models. The second sequential model, Sequential Model 2, utilizes an identical number of layers as Sequential Model 1. However, it is noteworthy that this model exhibits a considerable reduction in trainable parameters, with only 124,615 parameters compared to the other two models. The training accuracy of this model is recorded at 81.17%, with testing and validation accuracies of 81.35% and 80.21%, respectively. This indicates that Sequential Model 2 performs well, demonstrating efficient utilization of the model's capacity despite the reduced number of parameters.

CHAPTER 4

RESULT & DISCUSSION

4.1 Result and Discussion

We developed three CNN models and evaluated their performance using validation accuracies. The highest validation accuracy achieved was 79.85% with the first model, while the second and third models achieved 76.54% and 77.48%, respectively. These results suggest that the first model is the most effective for detecting skin cancer in the dataset we used.

Table 1 represents a comparison of the performance of three CNN models for image classification based on accuracy and number of parameters. The three models are a baseline CNN model, a Sequential CNN model (Model-1), and another Sequential CNN model (Model-2). The objective of the study was to determine the best performing model for accurate classification of skin cancer images.

TABLE 1: Comparison of the performance of CNN models

Models	Baseline CNN model	Sequential Model-1	Sequential Model-2
Training Accuracy	79.85	92.56	81.17
Testing Accuracy	76.54	92.12	81.35
Validation Accuracy	77.48	92.3	80.21
No. of Parameters	2,124,839	182,663	124,615

The training, testing, and validation accuracies of the models were evaluated. The baseline model had the lowest performance accuracy, with training accuracy of 79.85%, testing accuracy of 76.54%, and validation accuracy of 77.48%. Model-1 had the highest performance accuracy, with training accuracy of 92.56%, testing accuracy of 92.12%, and validation accuracy of 92.30%. Model-2 had training accuracy of 81.17%, testing accuracy of 81.35%, and validation accuracy of 80.21%.

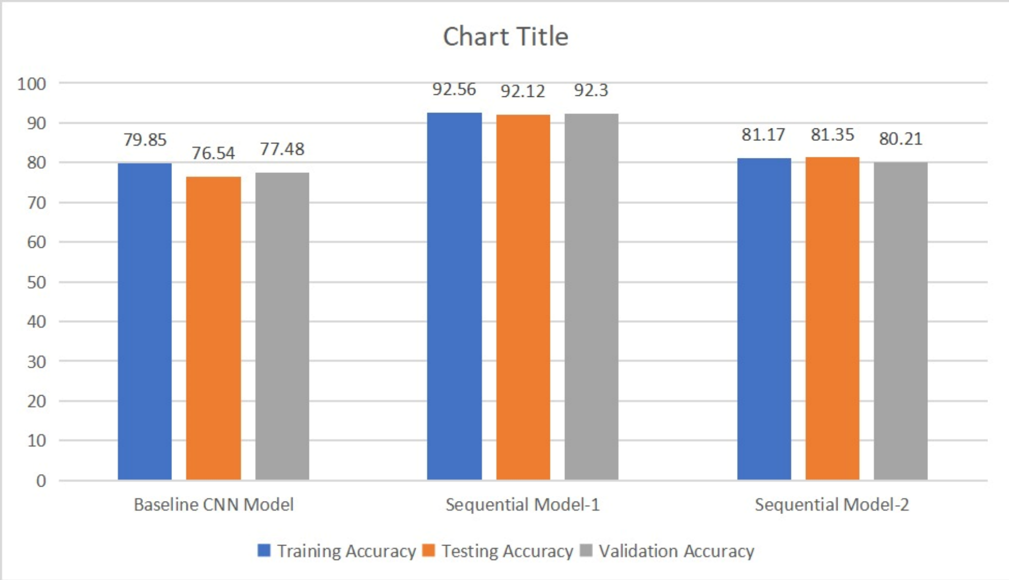

Figure 5. Performance comparison of deep learning models

The number of parameters used in each model was also evaluated. The baseline model had the highest number of parameters with 2,124,839, followed by Model-1 with 182,663 parameters, and Model-2 with 124,615 parameters. The number of parameters indicates the complexity of the model, with a higher number of parameters generally resulting in a more complex model. However, this does not always guarantee better performance accuracy.

The study also employed data augmentation techniques to reduce the problem of overfitting. The images in the dataset were rotated by 90 degrees clockwise and counter-clockwise, and flipped by 180 degrees and mixed with the original images. This was done to ensure an even distribution of the data in the dataset, without affecting the testing dataset.

The results of the study show that Model-1 had the highest performance accuracy, while Model-2 had the lowest performance accuracy. However, Model-2 had fewer parameters than Model-1, indicating a less complex model. Therefore, the choice of the best model for skin cancer image classification depends on the specific requirements and trade-offs between model complexity and performance accuracy. Overall, the study provides valuable insights into the use of CNN models for skin cancer image classification, and highlights the importance of data augmentation techniques in improving performance accuracy. Figure 6 shows the predicted output of Sequential Model -1 in which the prediction of Benign and Melanoma is around 99% and 76% respectively.

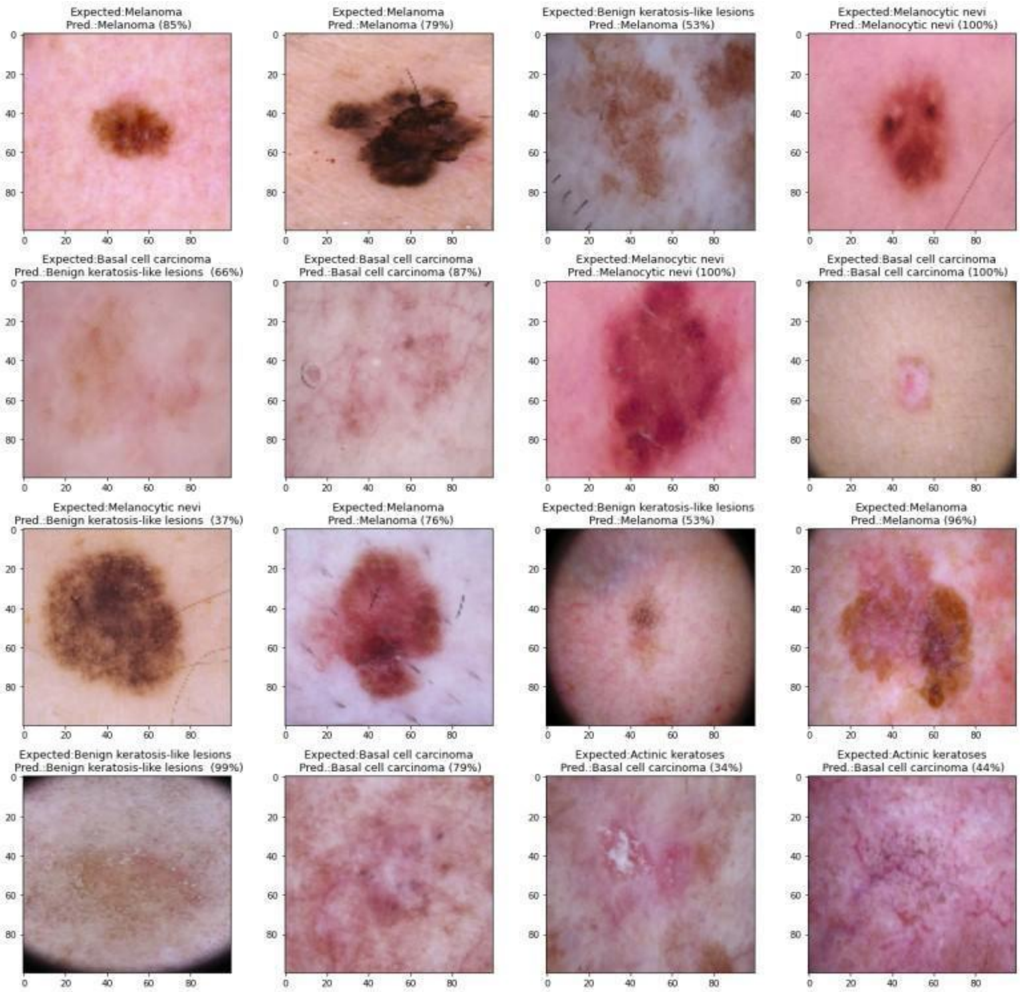

Figure 6. Prediction results of Sequential model - 1

CHAPTER 5

CONCLUSION

5.1 Conclusion

This study aims to explore the potential of using ensemble learning techniques in conjunction with various convolutional neural network (CNN) models to identify skin cancer using the HAM10000 skin cancer dataset. The primary focus of the investigation is to evaluate the accuracy of several CNN models and overcome the issue of overfitting by implementing data augmentation and preprocessing techniques.

The research demonstrates that the proposed methodology outperforms previous CNN models, showing significantly improved validation accuracy. This is a promising finding as it suggests that the use of ensemble learning techniques can contribute to earlier and more accurate skin cancer diagnosis, potentially resulting in life-saving interventions.

This research has significant implications for medical research, as it could provide physicians with a valuable tool in identifying skin cancer in its early stages. The use of advanced machine learning algorithms could assist in the early detection of skin cancer, which is critical in ensuring that patients receive timely and appropriate treatment. Furthermore, the proposed methodology could also be applied to other types of medical image analysis, broadening its scope of potential impact.

In conclusion, this study highlights the potential of ensemble learning techniques and CNN models in the field of medical image analysis. By employing advanced data augmentation and preprocessing techniques, the proposed methodology can overcome the challenge of overfitting and provide more accurate and reliable results. Ultimately, this research could contribute to earlier and more effective diagnosis of skin cancer, ultimately leading to better health outcomes for patients.

5.2 Future Scope

Deep learning algorithms, such as convolutional neural networks (CNNs), have demonstrated exceptional accuracy in the detection of skin cancer from medical images, leading to early diagnosis and treatment, with the potential to significantly enhance patient outcomes. The increasing availability of large annotated datasets and advancements in deep learning techniques are anticipated to further improve the accuracy and efficiency of skin cancer detection in the future.

One area of potential future research in skin cancer detection using deep learning is the development of more robust and interpretable models. Researchers are actively engaged in designing CNN architectures that can effectively handle diverse skin types, ages, and ethnicities, aiming to enhance the reliability and accuracy of skin cancer detection across a wide range of populations. Furthermore, efforts are being devoted to interpreting the decisions made by deep learning models, which could foster trust and understanding among clinicians and patients by elucidating the reasoning behind the model's predictions, thus rendering it more explainable and transparent.

Another promising avenue for future research is the integration of deep learning models into wearable devices, enabling real-time and continuous monitoring of skin lesions. This approach has the potential to facilitate the early detection of skin cancer at its initial stages, providing timely alerts to individuals and thereby improving the prospects of successful treatment.

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ANNEXURE – I

(PHOTOGRAPH OF CANDIDATES)

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ANNEXURE – II
(CERTIFICATES OF TECHNICAL COMPETITION)

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DEPARTMENT OF ELECTRONICS ENGINEERING

ENNOVATE ' 23

A National Level Project Competition

CERTIFICATE OF APPRECIATION

This is to certify that Mr./ Ms.

Siddhant Jain

has participated in <u>Project</u> competition on 5th April 2023.

Title of his/her Project is

Skin cancer Detection & Classification using Deep Learning

Prof. V. R. Rathee Convener	Prof. S. V. Laddha Convener	Dr. (Mrs.) M. A. Hasamnis Head of Department	Dr. R. S. Pande Principal

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SHRI RAMDEOBABA COLLEGE OF ENGINEERING AND MANAGEMENT, NAGPUR

DEPARTMENT OF ELECTRONICS ENGINEERING

ENNOVATE ' 23

A National Level Project Competition

CERTIFICATE OF APPRECIATION

This is to certify that Mr./ Ms.

Harsh Choubey

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Title of his/her Project is

Skin cancer Detection & Classification using Deep Learning

Prof. V. R. Rathee	Prof. S. V. Laddha	Dr. (Mrs.) M. A. Hasamnis	Dr. R. S. Pande
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