AarogyaMitra : An Automated Disease Diagnosis System

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***Abstract*—Recent research has seen an upsurge in the application of various supervised learning methods to develop automated diagnostic models. Timely detection of diseases holds promise in reducing mortality rates associated with these ailments. In this study, we propose the utilization of machine learning techniques to construct an efficient automated disease diagnosis system. Focusing on melanoma and brain tumors, two significant illnesses, our approach entails inputting data into an Android application. This application employs a pre-trained machine learning model, trained on a corresponding dataset, for real-time analysis in a database, and subsequently presents the diagnostic outcome within the Android app. Logistic regression is employed for predictive computation. Early detection aids in assessing the risk of conditions such as diabetes, heart disease, and coronavirus. Comparative analysis reveals that our proposed model can support healthcare professionals in offering timely therapeutic prescriptions.**

***Keywords*—Medical Diagnostic Systems, CNN, Melanoma, Brain Tumor**

I. Introduction

Skin cancer and brain tumors represent significant health challenges globally, impacting millions of lives annually. Skin cancer, characterized by abnormal cell growth in the skin, and brain tumors, arising from irregular cell proliferation within the brain, pose serious threats to individuals' health and well-being. Despite advances in medical technology, timely diagnosis and access to appropriate healthcare services remain critical in effectively managing these conditions. In response to these challenges, we propose a comprehensive research paper focusing on the development and implementation of an innovative mobile application aimed at enhancing healthcare accessibility and awareness. By providing timely and accurate diagnostic assessments, the application aims to facilitate early detection and intervention, ultimately improving patient outcomes

This article aims to provide an overview of the main points of this application, together with a special introduction of advanced technology for the diagnosis and distribution of skin cancer and mental illnesses. Thanks to the integration of advanced machine learning, the app allows users to submit skin images to diagnose various types of cancer and look at brain MRI to identify different types of brain tumors. The app aims to facilitate early detection and intervention by providing timely and accurate screening, ultimately improving patient outcomes. These machine learning models are trained from large datasets of descriptive images, allowing them to identify and classify abnormalities in skin and brain tumors with accuracy and confidence.

Machine learning models for skin cancer diagnosis are trained on data containing images of benign and malignant skin, including melanoma. This model not only detects skin cancer, but can also classify cells diagnosed as benign, malignant or non-cancerous growths. Similarly, machine learning models for brain tumor diagnosis have been trained on MRI images of a variety of brain tumors, including gliomas, meningiomas, pituitary tumors, and brain tumors. In addition to accurately identifying and characterizing these tumors, the model is also able to identify non-tumor conditions.
The main results of this study are summarized as follows:

1. Using machine learning techniques to create effective diagnostic models.
2. Focus on diagnosing two important diseases: brain cancer and melanoma (skin cancer).
3. The proposed model will involve data input from an Android application and then use a machine learning model for real-time analysis of the data. The model was trained on the same data.
4. Forecast calculation is done using logistic regression.

The following section offers a comprehensive review of existing literature on Machine learning algorithms used for training models to diagnose different diseases in the medical sector and also showcases the performance measures for each of the models. Section 3 outlines the specifics of the proposed algorithm. Section 4 presents a comprehensive array of experiments aimed at evaluating the efficacy of the approach. Finally, Section 5 offers concluding remarks and delves into prospective directions for future research initiatives.

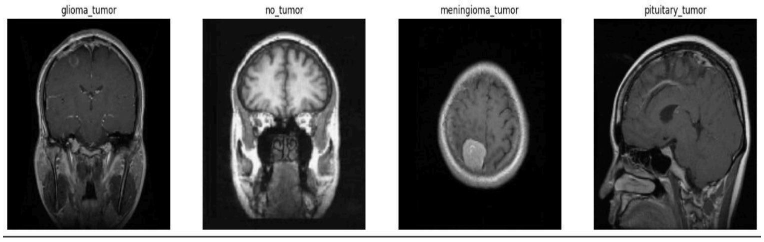
II. Related work

Recent developments in healthcare management have been marked by advances in technology integration, particularly in the field of health information management. Bali et al. [4] highlight the importance of patient information to inform clinical decisions and self-treatment, thereby improving patient outcomes. Sivasankari et al. [4] introduced an automated healthcare management system using big data that not only improves the quality of data by converting plain text into structured data but also promotes better healthcare. Moreover, Kumar and Dutt [6] proposed the use of machine learning models, especially the random forest method, to improve health information that obtains and verifies patient health information. Subramani et al. [1] demonstrated a change in the prediction of heart disease by increasing disease from a combination of models combining various machine learning methods, such as gradient-boosted decision trees (GBD). Additionally, Zhang et al. [2] about the evolution of artificial intelligence and machine learning in cancer research, particularly in prediction, prognosis and treatment options, helping with early diagnosis and self-treatment planning. Lee et al. [3] proposed a reinforcement learning algorithm model to improve clinical strategies using electronic health records (EHRs) for deep Q networks, including physical conditions and specific diseases. Meanwhile, recent literature has made significant advances in disease diagnosis and diagnosis through the integration of machine learning and deep learning models with various medical treatments.

Table 1: Comparative analysis of existing techniques

Year	Model Used	Detailed Features	Application
2018	CNN, VGG16, VGG19, ResNet50, InceptionV3, and Xception	MRI scans	Brain tumor detection
2019	CNN, SVM, and MLP	MRI scans	Brain tumor detection
2020	CNN, SVM, and MLP	Dermoscopic images	Melanoma detection
2021	CNN, SVM, KNN, Random Forest, Naive Bayes, Decision Tree, and MLP	Magnetic Resonance Imaging (MRI), enhancement techniques	Cancer detection
2022	Various ML and DL models	Detection and classification of multiple diseases	Medical diagnosis
2023	CNN	Dermoscopic images	Early detection of melanoma and brain tumors
2023	Various ML and DL models (CNN, SVM, KNN, Random Forest, Naive Bayes, Decision Tree, MLP)	Clinical data and medical images	Disease prediction and diagnosis

CNN, VGG16, VGG19, ResNet50, InceptionV3, and Xception models have been employed for brain tumor detection using MRI scans in [11] and [12]. Moreover, in [13], CNN, SVM, and MLP models were utilized for



melanoma detection through dermoscopic images.The year 2021 witnessed the deployment of a range of machine learning algorithms, including CNN, SVM, KNN, Random Forest, Naive Bayes, Decision Tree, and MLP, for cancer detection via Magnetic Resonance Imaging (MRI) and enhancement techniques[14]. In 2022, various ML and DL models were utilized for the detection and classification of multiple diseases, further advancing medical diagnosis[9]. Continuing this trajectory, in 2023, CNN models were employed for the early detection of melanoma and brain tumors through dermoscopic images, while various ML and DL models were utilized for disease prediction and diagnosis using clinical data and medical images[10]. Collectively, these studies highlight the pivotal role of technological integration, machine learning, and AI in revolutionizing healthcare delivery, from enhancing medical record management to advancing disease prediction, diagnosis, and treatment optimization.

III. Methodology

The app aims to improve patient outcomes and empower people to take control of their health by using advanced technology for skin and brain diseases. Figure 1 shows a simple, step-by-step diagram of a machine learning model. First of all, data cleaning is performed to transform the raw data into a usable form. After the data was cleaned, data analysis was performed to determine the significance of the features. In data analysis, features are determined and the data is converted into a form that machine learning can use. These steps apply to all predictive models: (a) Brain tumor(b) Melanoma - Cancer.

(a) In this section, we first propose a method to classify brain tumors using deep learning transformation. Study techniques applied to MRI images. Our approach involves several important steps in building and training the classification model. First, we prepared a database containing MRI images representing different brain tumors, including gliomas, meningiomas, pituitary tumors, and benign tumors, as shown in Figure 2. It was first done using OpenCV by changing the lengths according to the model and assigning labels to each tumor type accordingly. The entire dataset is then split into a training and a testing as shown in Figure 3. We then use transformation learning with the EfficientNetB0 model using pre-learning weights from the ImageNet dataset. By excluding the upper layers, we cut the model for the classification function so that it can be used as a material for learning the features of MRI images.

We add layers on top of previous layers to create the architectural model. - Efficient learning model EfficientNetB0. This includes the GlobalAveragePooling2D layer to reduce generalization, the Dropout layer to reduce competition, and the Dense layer with softmax to increase distribution. The model is then compiled using appropriate unemployment,optimization and evaluation methods. Use sample collection and data preparation for training and use current data to monitor performance. We use various callbacks such as TensorBoard, ModelCheckpoint, and DifferentLROnPlateau to track the training progress, save the best model, and update the learning rate.

Use indicators such as accuracy, precision, and recall to evaluate the model's performance after training. F1 group. Visualization tools like TensorBoard help understand the behavior of the model and identify potential problems such as overuse. Our approach provides a way to build and train classification models of brain tumors by leveraging adaptive learning and deep learning to obtain accurate and reliable results.

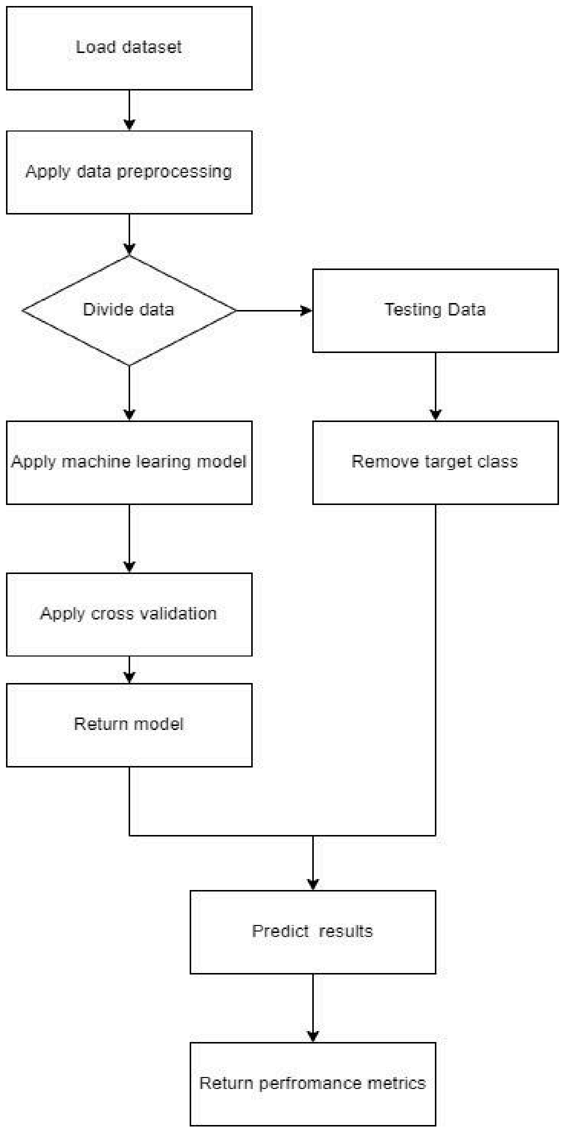


Figure 1 : Flowchart of basic machine learning model

Figure 2 : Brain tumor dataset sample

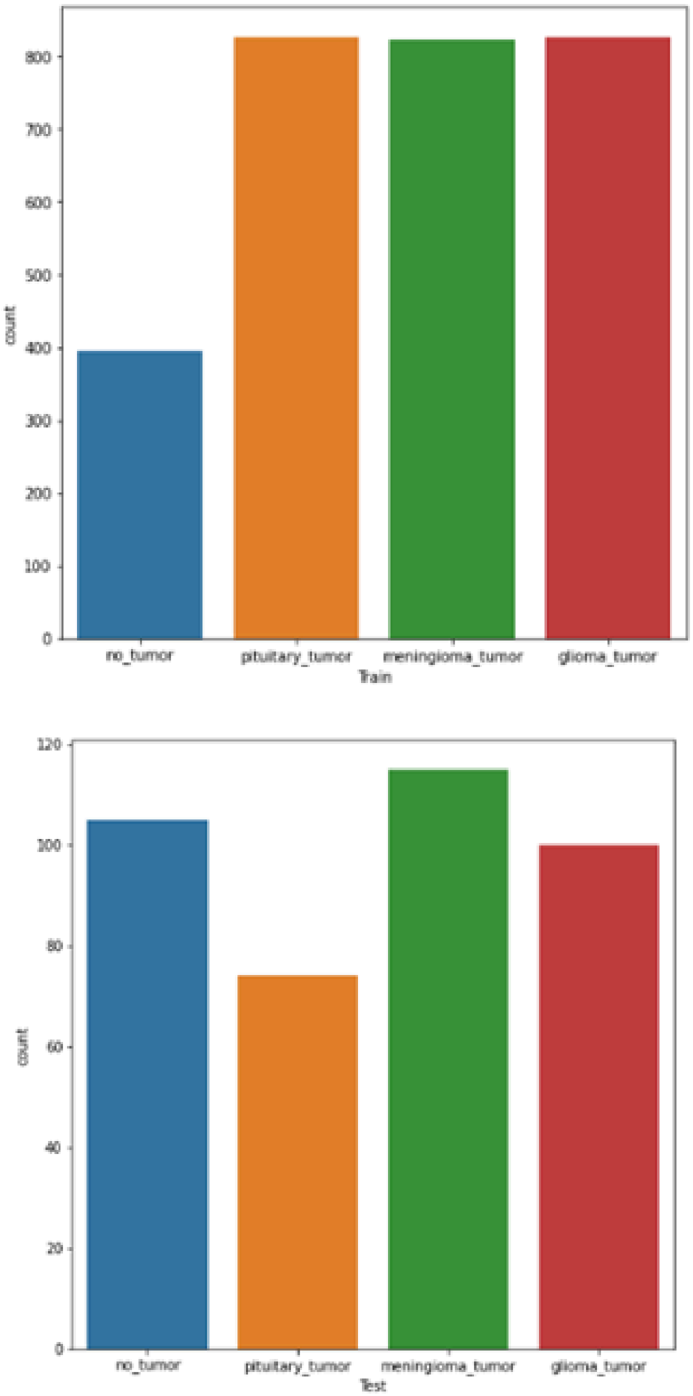


Figure 3 : Splitting the data into training and testing dataset

(b) Automatic classification of skin lesions using images is a difficult task due to the fine-grained variability in skin lesion appearance. The process consists of several important steps aimed at analyzing skin cancer data and developing a good classification model. First of all, the process starts by getting good information about skin cancer from reliable sources such as Kaggle. The image is converted to low resolution (224x224x3) RGB. There are 2 types of skin cancer listed below:
1. Benign 2. Malignant

Basic pre-processing steps need to import appropriate files such as NumPy, Matplotlib, Pandas and TensorFlow/Keras for data processing and analysis. Data is typically stored in CSV files uploaded using Pandas, allowing access to pixel data and associated tags. The next profile search involves visualizing the distribution of the profile to identify class anomalies that are important for subsequent analysis. Data augmentation is used to resolve uncertainty in the classroom. Use Keras' ImageDataGenerator to create new images by performing transformations such as rotating, shifting, and rotating. Additionally, duplicate data for various classes are used to balance the dataset, and the best results are selected to focus on improved data.

Training neural networks for automatic diagnosis of pigmented skin suffers from small data and lack of diversity in dermoscopic images. This problem was solved using the HAM10000 ("humans and machines with 10,000 training images") dataset. These files collect dermoscopy images and store them in different ways for different people. The final dataset contains 10,015 dermoscopic images that can be used for machine learning. Data included representative samples from all major diagnostic groups. Areas of pigmented lesions: actinic keratosis and intraepithelial carcinoma/Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar freckles/seborrheic keratosis and keratosis lichen planus, bkl), cutaneous fibromyopathy) and vascular disease (hemangioma).), angiokeratoma, pyogenic granuloma and hemorrhage, hemangioma). More than 50% of lesions were confirmed histopathologically; Important patient specific details confirmed by clinical examination, examination or intravital confocal microscopy. This file contains lesions with multiple images, which can be tracked by the lesion_id field in the HAM10000_metadata file.

Table 2 : Skin Cancer Dataset Metadata

image_ id	dx	dx_ type	age	sex	Localization
ISIC_00274 19	bkl	histo	80.0	male	scalp
ISIC_00250 30	bkl	histo	80.0	male	scalp
ISIC_00267 69	bkl	histo	80.0	male	scalp
ISIC_00256 61	bkl	histo	80.0	male	scalp
ISIC_00316 33	bkl	histo	75.0	male	ear

Once you receive the resized file, clean up the file by deleting the file that is not suitable for use. Then the data set is divided into reference data, valid data and test data according to 80:10:10.

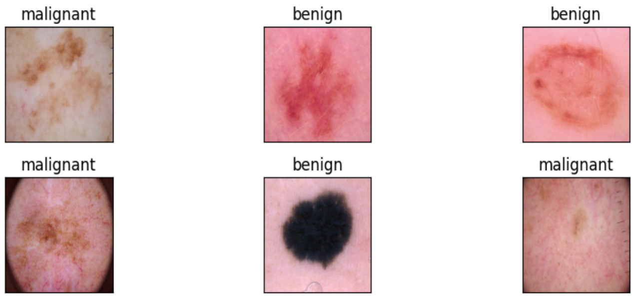


Figure 4: Skin Cancer – Melanoma Dataset

Deep network (ResNet) is a neural network designed to solve the problem of creating a traditional ANN with deeper layers than a shallow ANN. In other words, the goal of deep networking is to make neural networks with deeper layers and more accurate. The idea of the Deep Residual Network is to enable the ANN to adjust the weights of the layers (minimizing degenerate gradients). The idea is to use "quick connect".

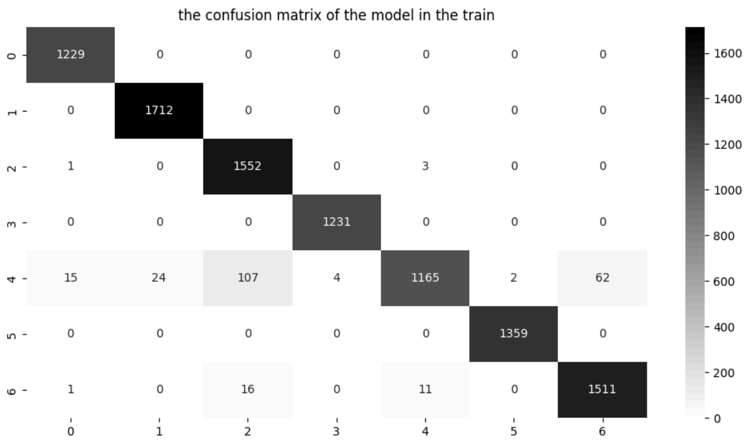
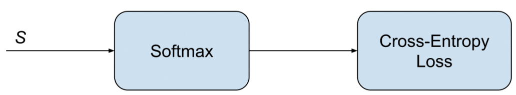


Figure 5 : Confusion Matrix of Skin Cancer Dataset

We use adaptive learning for classification of skin lesions by slightly modifying the design and adjusting the weights of the ResNet50 model before training on the ImageNet dataset. Changes include using global average pooling instead of average pooling. Hyperparameters are important when they directly affect the behavior of the system because well-tuned hyperparameters are related to the output of the model. We use the Adam optimizer to train 10 times and set the learning rate to 0.0001 for a group of 32 people. Additionally, the categorical cross-entropy loss function given below calculates the probability of class loss predicted by the eye maximum function. Finally, evaluate the results of each category.



$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}} \quad CE = -\sum_i^C t_i log(f(s)_i)$$

IV. Implementation and Results

(a) Melanoma – Skin Cancer

This paper investigated the efficacy of various machine learning techniques for Skin cancer detection. The evaluation focused on accuracy, sensitivity, specificity, and, in certain cases, Mean Absolute Percentage Error (MAPE). Deep learning architectures emerged as the frontrunners in terms of accuracy. The custom-designed DenseNet model stood out with a remarkable accuracy of 98.52%. This signifies its exceptional ability to learn complex patterns within your data. Following closely behind was the ensemble approach combining SVM and CNN, achieving an accuracy of 92.00%. This finding suggests that strategically combining different algorithms can lead to significant performance gains. Interestingly, the combination of SVM and ANN (another ensemble method) yielded an even higher accuracy (96.8%) compared to using either technique independently (SVM: 89.43%, ANN: 86.3%). This reinforces the notion that ensemble methods leveraging the strengths of multiple algorithms can be highly effective.

Among other techniques, KNN achieved a moderate accuracy of 69.54%, while Random Forest obtained 76.87%. However, it's crucial to consider the trade-off between sensitivity and specificity for these approaches. KNN exhibited a MAPE of 0.71, indicating a reasonable level of error in its predictions. SVM offered a high sensitivity of 91.15%, suggesting its proficiency in identifying positive cases. However, its specificity was slightly lower at 87.71%. In contrast, Random Forest displayed a more balanced performance with a sensitivity of 78.43% and a specificity of 75.31%.

Key Takeaways and Future Directions

This study underscores the remarkable potential of deep learning and ensemble methods for achieving exceptional accuracy in the domain of [your research topic]. The custom-built DenseNet model and the combined SVM-CNN approach demonstrate the power of these techniques in uncovering intricate relationships within your data. Additionally, the success of the SVM-ANN ensemble highlights the value of strategically combining algorithms for improved performance. While KNN and Random Forest achieved moderate accuracy, their performance highlights the importance of considering both sensitivity and specificity depending on the specific application. SVM's strength lies in its ability to detect positive cases, while Random Forest offers a more balanced approach.

Table 3 : Comparison of different mode;s for skin cancer

No.	Technique/ Algorithm	Evaluation metrics
1	KNN	**MAPE** of 0.71
2	SVM, KNN, RF	**Accuracy (%)** SVM: 89.43,RF: 76.87, KNN: 69.54 **Sensitivity (%)** SVM:91.15, RF:78.43,KNN:71.32 **Specificity(%)** SVM:87.71,RF:75.31,KNN: 67.76
3	SVM and CNN	**Accuracy (%)** = 92.00
4	Deep Learning and Fuzzy K-Means Clustering	**Accuracy** = 95.40% **Specificity** = 97.10%, **Sensitivity** = 90.00%
5	RCNN	**Accuracy** = 94.8%, **Specificity** = 94.17%, **Sensitivity** = 97.81% **F1_score** = 95.8%
6	ResFCN	**Accuracy** = 94.29%, **Specificity** = 93.05%, **Sensitivity** = 93.77%
7	ANN	**Accuracy** = 86.3%, **Specificity** = 86.9%, **Sensitivity** = 87.8%
8	SVM and ANN	**Accuracy** = 96.8%, **Specificity** = 89.3%, **Sensitivity** = 95.4%

Note : Source Aarushi Shah et.al [15]

For example: There are two instances of glioma_tumor being misclassified as meningioma_tumor, one instance of glioma_tumor being misclassified as pituitary_tumor, one instance of meningioma_tumor being misclassified as glioma_tumor, one instance of meningioma_tumor being misclassified as pituitary_tumor, one instance of pituitary_tumor being misclassified as meningioma_tumor. The validation performance depicted in the accuracy and loss curves illustrates a consistent

(b) Brain Tumor.

Our brain tumor classification model, leveraging transfer learning with EfficientNetB0, has yielded remarkable results, boasting an overall accuracy of approximately 98%. This accuracy underscores the efficacy of our model in accurately classifying brain tumor images. The precision, recall, and F1-score metrics provide further insight into the model's performance, with scores ranging from 0.97 to 1.00 across different tumor classes. Notably, our model achieves perfect precision and recall for "No Tumor" cases, showcasing its reliability in identifying healthy brain scans.

From the heatmap (Fig. 6), it seems the model is performing relatively well as most of the counts are concentrated on the diagonal, indicating correct predictions. However, there are a few misclassifications, which are indicated by the off-diagonal cells. For improvement over epochs, indicating the model's effective learning process and adaptability to the dataset. Moreover, the confusion matrix reveals minimal misclassifications, demonstrating the model's proficiency in accurately categorizing brain tumor images and its ability to minimize false positives and negatives.

In comparison with other standard models, our model stands out for its superior accuracy and precision, highlighting its potential as a valuable tool in medical image analysis. Its high performance suggests its suitability for clinical applications, such as aiding in the diagnosis and treatment planning for brain tumors, thereby potentially contributing to improved patient outcomes.

Continued refinement through techniques like fine-tuning or ensemble learning could further enhance our model's performance, solidifying its position as a reliable and effective solution in the field of medical imaging. Furthermore, exploring interpretability methods could provide insights into the decision-making process of the model, enhancing trust and understanding among healthcare professionals.

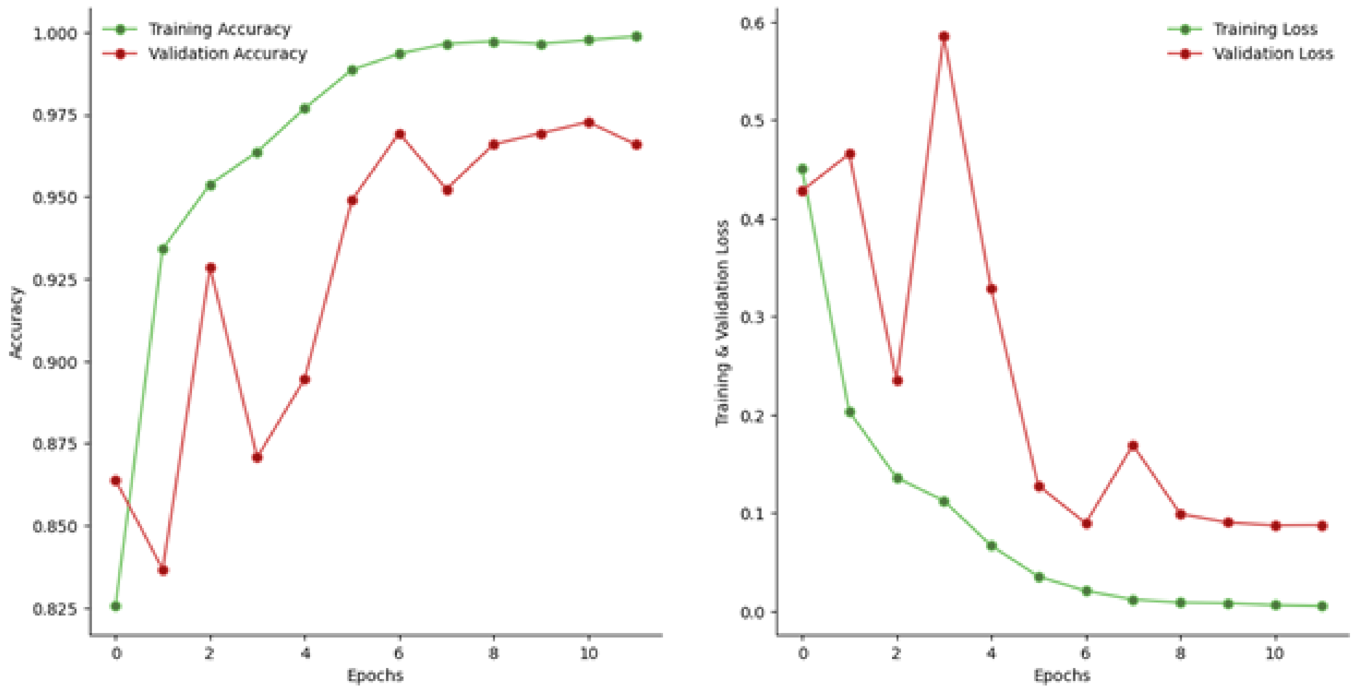


Figure 6 : Epochs vs. Training and Validation Accuracy/Loss

V. CONCLUSION

In conclusion, the paper titled "AarogyaMitra: An Automated Disease Diagnosis System" presents an innovative approach utilizing advanced machine learning techniques for automated disease diagnosis, focusing particularly on skin cancer (melanoma) and brain tumors. Through the development of an Android application integrated with machine learning models trained on large datasets, the system aims to enable early detection and intervention, thereby improving patient outcomes. The proposed methodology involves data input via the Android app, real-time analysis using pre-trained machine learning models deployed on Firebase, and display of diagnosis results within the app. Logistic regression is employed for prediction computation. The paper provides a comprehensive review of existing literature on machine learning algorithms for medical diagnosis and showcases the performance measures of various models.

Experimental results demonstrate the efficacy of deep learning architectures and ensemble methods in achieving high accuracy for skin cancer detection and brain tumor classification. The proposed models outperform traditional algorithms, indicating their potential for clinical applications.

Key contributions of the paper include the development of efficient automated disease diagnosis models, particularly for melanoma and brain tumors, and the utilization of advanced machine learning techniques within a user-friendly mobile application. The results underscore the transformative potential of machine learning and AI in revolutionizing healthcare delivery, from enhancing medical record management to advancing disease prediction, diagnosis, and treatment optimization.

Future research directions include continued refinement of the proposed models through techniques like fine-tuning and ensemble learning, as well as exploration of interpretability methods to enhance trust and understanding among healthcare professionals. Overall, the paper presents a promising approach towards leveraging technology to address critical healthcare challenges and improve patient outcomes.

References

[1] Subramani S, Varshney N, Anand MV, Soudagar MEM, Al-Keridis LA, Upadhyay TK, Alshammari N, Saeed M, Subramanian K, Anbarasu K, Rohini K. Cardiovascular diseases prediction by machine learning incorporation with deep learning. Front Med (Lausanne). 2023 Apr 17;10:1150933. doi: 10.3389/fmed.2023.1150933. PMID: 37138750; PMCID: PMC10150633.

[2] Zhang B, Shi H, Wang H. Machine Learning and AI in Cancer Prognosis, Prediction, and Treatment Selection: A Critical Approach. J Multidiscip Healthc. 2023 Jun 26;16:1779-1791. doi: 10.2147/JMDH.S410301. PMID: 37398894; PMCID: PMC10312208.

[3] Tianhao Li, Zhishun Wang, Wei Lu, Qian Zhang, Dengfeng Li, Electronic health records based reinforcement learning for treatment optimizing, Information Systems, Volume 104, 2022, 101878,ISSN 0306-4379, https://doi.org/10.1016/j.is.2021.101878.

[4] Bali A, Bali D, Iyer N, Iyer M. Management of medical records: facts and figures for surgeons. J Maxillofac Oral Surg. 2011 Sep;10(3):199-202. doi: 10.1007/s12663-011-0219-8. Epub 2011 Apr 20. PMID: 22942587; PMCID: PMC3238553.

[5] Sivasankari, Ms & Sindhuja, Mrs & Selvakani, Mrs & Arunachalam, Sivasankari. (2021). AUTOMATED HEALTH CARE MANAGEMENT SYSTEM USING BIG DATA TECHNOLOGY. 10.13140/RG.2.2.34498.09928.

[6] Kumar, Abhishek & Sairam, Tvm & Dutt, Vishal. (2018). MACHINE LEARNING IMPLEMENTATION FOR SMART HEALTH RECORDS: A DIGITAL CARRY CARD. 1-2019.

[7] Kumar N, Narayan Das N, Gupta D, Gupta K, Bindra J. Efficient Automated Disease Diagnosis Using Machine Learning Models. J Healthc Eng. 2021 May 4;2021:9983652. doi: 10.1155/2021/9983652. PMID: 34035886; PMCID: PMC8101482.

[8] Bakator, Mihalj & Radosav, Dragica. (2018). Deep Learning and Medical Diagnosis: A Review of Literature. Multimodal Technologies and Interaction. 2. 47. 10.3390/mti2030047.

[9] Khan, Muneeb A., and Heemin Park. 2024. "A Convolutional Block Base Architecture for Multiclass Brain Tumor Detection Using Magnetic Resonance Imaging" Electronics 13, no. 2: 364. https://doi.org/10.3390/electronics13020364

[10] Kujani, T., Alex David, S., Sathya, T., Arivubrakan, P., Shanmuga Priya, S. (2023). Efficient Brain Tumor Detection Using VGG-16 and ResNet50 Transfer Learning Models. In: Ranganathan, G., EL Allioui, Y., Piramuthu, S. (eds) Soft Computing for Security Applications. ICSCS 2023. Advances in Intelligent Systems and Computing, vol 1449. Springer, Singapore. https://doi.org/10.1007/978-981-99-3608-3_32

[11] Kamal Kamal, Hamid EZ-ZAHRAOUY.(27 April 2023) A comparison between the VGG16, VGG19 and ResNet50 architecture frameworks for classification of normal and CLAHE processed medical images,, PREPRINT (Version 1) available at Research Square [https://doi.org/10.21203/rs.3.rs-2863523/v1]

[12] Khan MSI, Rahman A, Debnath T, Karim MR, Nasir MK, Band SS, Mosavi A, Dehzangi I. Accurate brain tumor detection using deep convolutional neural network. Comput Struct Biotechnol J. 2022 Aug 27;20:4733-4745. doi: 10.1016/j.csbj.2022.08.039. PMID: 36147663; PMCID: PMC9468505.

[13] Alwakid G, Gouda W, Humayun M, Sama NU. Melanoma Detection Using Deep Learning-Based Classifications. Healthcare (Basel). 2022 Dec 8;10(12):2481. doi: 10.3390/healthcare10122481. PMID: 36554004; PMCID: PMC9777935.

[14] Nusrat Mohi ud din, Rayees Ahmad Dar, Muzafar Rasool, Assif Assad,Breast cancer detection using deep learning: Datasets, methods, and challenges ahead,Computers in Biology and Medicine,Volume149,2022,106073,ISSN0010-4825,https://doi.org/10.1016/j.compbiomed.2022.106073.

[15] Aarushi Shah, Manan Shah, Aum Pandya, Rajat Sushra, Ratnam Sushra, Manya Mehta, Keyur Patel, Kaushal Patel,A comprehensive study on skin cancer detection using artificial neural network (ANN) and convolutional neural network (CNN),Clinical eHealth,Volume 6,2023,Pages 76-84,ISSN 2588-9141,https://doi.org/10.1016/j.ceh.2023.08.002.