VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

An Autonomous Institute Affiliated to University of Mumbai

Department of Computer Engineering

Project Report on

AarogyaMitra : An Automated Disease Diagnosis System

In partial fulfillment of the Fourth Year, Bachelor of Engineering (B.E.) Degree in Computer Engineering at the University of Mumbai Academic Year 2023-24

Submitted by

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(2023-24)

VIVEKANAND EDUCATION SOCIETY'S INSTITUTE OF TECHNOLOGY

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Certificate

This is to certify that ***Sakshi Rane(D17B, 59), Reshoo Nehru(D17B, 48) Tarang Rajpal(D17B, 58)*** of Fourth Year Computer Engineering studying under the University of Mumbai have satisfactorily completed the project on "***AAROGYA MITRA : HEALTH DIAGNOSIS APP***" as a part of their coursework of PROJECT-II for Semester-VIII under the guidance of their mentor ***Prof. Sunita Suralkar*** in the year 2023-24 .

This project report entitled **Aarogyamitra : Health Diagnosis App** by **Sakshi Rane**, **Reshoo Nehru**, **Tarang Rajpal** is approved for the degree of **B.E. Computer Engineering**.

Programme Outcomes	Grade
PO1,PO2,PO3,PO4,PO5,PO6,PO7, PO8, PO9, PO10, PO11, PO12 PSO1, PSO2	

Date:

Project Guide:

Project Report Approval

For

B. E (Computer Engineering)

This project report entitled ***AarogyaMitra : Health Diagnosis App*** by (***Sakshi Rane, Reshoo Nehru, Tarang Rajpal***) is approved for the degree of **B.E. Computer Engineering**.

Internal Examiner

External Examiner

Head of the Department

Principal

Date:

Place: Mumbai

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Sakshi Rane (59)	Reshoo Nehru (48)

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Date:

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We are deeply indebted to the Head of the Computer Department **Dr. (Mrs.) Nupur Giri** and our Principal **Dr. (Mrs.) J.M. Nair ,** for giving us this valuable opportunity to do this project.

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We convey our deep sense of gratitude to all teaching and non-teaching staff for their constant encouragement, support and selfless help throughout the project work. It is a great pleasure to acknowledge the help and suggestion, which we received from the Department of Computer Engineering.

We wish to express our profound thanks to all those who helped us in gathering information about the project. Our families too have provided moral support and encouragement several times.

Computer Engineering Department
COURSE OUTCOMES FOR B.E PROJECT

Learners will be to,

Course Outcome	Description of the Course Outcome
CO 1	Able to apply the relevant engineering concepts, knowledge and skills towards the project.
CO2	Able to identify, formulate and interpret the various relevant research papers and to determine the problem.
CO 3	Able to apply the engineering concepts towards designing solutions for the problem.
CO 4	Able to interpret the data and datasets to be utilized.
CO 5	Able to create, select and apply appropriate technologies, techniques, resources and tools for the project.
CO 6	Able to apply ethical, professional policies and principles towards societal, environmental, safety and cultural benefit.
CO 7	Able to function effectively as an individual, and as a member of a team, allocating roles with clear lines of responsibility and accountability.
CO 8	Able to write effective reports, design documents and make effective presentations.
CO 9	Able to apply engineering and management principles to the project as a team member.
CO 10	Able to apply the project domain knowledge to sharpen one's competency.
CO 11	Able to develop a professional, presentational, balanced and structured approach towards project development.
CO 12	Able to adopt skills, languages, environment and platforms for creating innovative solutions for the project.

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Abstract

Many researchers have recently used a variety of supervised learning techniques to create a range of automated diagnosis models. Early disease detection could reduce the number of people who die from these conditions. This research uses machine learning models to develop an effective automated disease diagnostic algorithm. We have chosen two serious illnesses, including melanoma and brain tumors, for this essay.

“AarogyaMitra” involves entering the data into an Android app, utilizing a pre trained machine learning model that was trained on the same dataset and deployed on SQLite for analysis in a real-time database, and ultimately displaying the illness detection result in the Android app. The prediction computation is done using logistic regression. Determining the risk of tumor and skin disease can be aided by early detection. A comparative investigation shows that the suggested model can assist laymen and medical professionals in providing timely prescriptions for therapy.

Chapter 1: Introduction

1.1. Introduction

This paper aims to outline the key components of the application, particularly highlighting the utilization of advanced machine learning models for skin cancer and brain tumor detection and classification. Through the integration of advanced machine learning algorithms, the application offers users the ability to upload skin images for the diagnosis of various types of skin cancer and brain MRI top view scans for the identification of different types of brain tumors. By providing timely and accurate diagnostic assessments, the application aims to facilitate early detection and intervention, ultimately improving patient outcomes. These machine learning models have been trained on large datasets of annotated images, enabling them to accurately identify and classify abnormalities indicative of skin cancer and brain tumors with high precision and reliability.

For skin cancer detection, the machine learning model is trained on a dataset comprising images of benign and malignant skin lesions, including melanoma. The model not only diagnoses the presence of skin cancer but also classifies the detected lesions into benign, malignant, or no cancerous growth. Similarly, for brain tumor detection, the machine learning model is trained on MRI images depicting different types of brain tumors, including glioma tumor, meningioma tumor, pituitary tumor, and normal brain scans. The model is capable of accurately identifying and classifying these tumors, as well as detecting cases where no tumor is present.

1.2. Motivation

The motivation behind our Health Diagnosis App stems from recognizing the profound impact of Machine Learning (ML) on modern healthcare. In a rapidly evolving landscape where technology plays a pivotal role, leveraging ML presents an opportunity to revolutionize medical diagnostics and treatment. Traditional healthcare systems often struggle with the efficient processing of vast patient data and staying updated with the latest medical knowledge. Thus, our project seeks to bridge this gap by developing an innovative solution that not only addresses current challenges but also anticipates future needs. Through the integration of ML algorithms, our app aims to enhance the precision and efficiency of medical diagnoses, offering healthcare professionals a powerful tool for timely decision-making.

1.3. Problem Definition

The conventional approach to managing patient health records and analyzing medical reports faces significant limitations, including inefficiencies in data storage, retrieval, and analysis.
AarogyaMitra app aims to establish individual accounts for patients, facilitating secure storage of their medical reports and provide sophisticated analysis of the report data using ML techniques.
Our goal is to provide easy-to-understand health insights that anyone can use to make informed decisions about their well-being.

1.4. Existing Systems

Recent advancements in healthcare management systems have been marked by a surge in technological integration, particularly within the realm of medical record management. Bali, et al. [4] underscore the significance of detailed patient records in facilitating informed treatment decisions and personalized care adjustments, thereby enhancing patient outcomes. Sivasankari, et al. [4] introduce an Automated Health Care Management System leveraging big data technology, which not only enhances data quality through the conversion of free-text reports into structured formats but also streamlines healthcare operations for improved accessibility. Additionally, Kumar and Dutt [6] advocate for the implementation of machine learning models, specifically utilizing the random forest methodology, to organize acquired health data efficiently and accurately detect patient health information. Subramani, et al. [1] contribute to disease prediction with a stacking model incorporating various machine learning techniques, such as Gradient Boosted Decision Trees (GBDT), showcasing adaptability in predicting cardiovascular diseases. Furthermore, Zhang, et al. [2] underscore the transformative impact of AI and ML in cancer research, particularly in prognosis, prediction, and treatment selection, aiding in early detection and personalized treatment plans.

1.5. Lacuna of the existing systems

Lack of Medical Professional Involvement:

One prominent lacuna in existing health diagnosis apps is the limited involvement of qualified medical professionals in the development and validation process. While many apps claim to offer accurate diagnoses and medical advice, their algorithms and databases are often constructed without sufficient input from healthcare experts.

Limited Diagnostic Accuracy and Specificity:

Despite their widespread use, many health diagnosis apps demonstrate suboptimal diagnostic accuracy and specificity, particularly when compared to traditional clinical assessments. These apps often rely on simplistic algorithms and generic symptom-checking mechanisms, which may overlook nuanced or atypical presentations of medical conditions.

Inadequate Privacy and Data Security Measures:

Privacy and data security represent significant concerns associated with health diagnosis apps, with many applications failing to implement robust measures to protect user data. Given the sensitive nature of health information, the potential risks associated with data breaches or unauthorized access are considerable.

Limited Accessibility and Equity:

Accessibility and equity issues pose additional challenges in the utilization of health diagnosis apps, particularly for underserved populations and individuals with limited digital literacy or access to technology. Many existing apps are designed with assumptions of user proficiency and access to high-speed internet, thereby excluding segments of the population who may benefit most from such tools.

1.6 Relevance of the Project

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

Chapter 2: Literature Survey

2.1. Research Papers Referred

1.Kumar N, Narayan Das N, Gupta D, Gupta K, Bindra J. Efficient Automated Disease Diagnosis Using Machine Learning Models. J Healthc Eng. 2021 May

a) Abstract

Recently, many researchers have designed various automated diagnosis models using various supervised learning models. An early diagnosis of disease may control the death rate due to these diseases. In this paper, an efficient automated disease diagnosis model is designed using the machine learning models. In this paper, we have selected three critical diseases such as coronavirus, heart disease, and diabetes. In the proposed model, the data are entered into an android app, the analysis is then performed in a real-time database using a pretrained machine learning model which was trained on the same dataset and deployed in firebase, and finally, the disease detection result is shown in the android app.

b) Inference

This study provides insights into using the machine learning models to predict the risk of COVID-19, heart disease, and diabetes in an individual based on answering a few questions related to various factors like travel history, age, gender, and blood pressure. Logistic regression is used for prediction. Extensive experimental results reveal that the proposed model outperforms the competitive machine learning models in terms of accuracy and F-measure by 1.4765% and 1.2782, respectively, for COVID-19 dataset.

2.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

a) Abstract

It is yet unknown what causes cardiovascular disease (CVD), but we do know that it is associated with a high risk of death, as well as severe morbidity and disability. There is an urgent need for AI-based technologies that are able to promptly and reliably predict the future outcomes of individuals who have cardiovascular disease. The Internet of Things (IoT) is serving as a driving force behind the development of CVD prediction. In order to analyse and make predictions based on the data that IoT devices receive, machine learning (ML) is used. Traditional machine learning algorithms are unable to take differences in the data into account and have a low level of accuracy in their model predictions. This research presents a collection of machine learning models that can be used to address this problem.

b) Inference

The study builds a stacking model with base learners (RF, LR, MLP, ET, CatBoost) and a meta learner (LR). It evaluates this model's performance using metrics like accuracy, precision, recall, F1 score, and AUC and assesses its adaptability to new contexts with the Heart Attack Dataset.
It employs the Gradient Boosted Decision Trees (GBDT) method for feature selection.

3.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

a) Abstract

Detection and Classification of a brain tumor is an important step to better understanding its mechanism. Magnetic Reasoning Imaging (MRI) is an experimental medical imaging technique that helps the radiologist find the tumor region. However, it is a time taking process and requires expertise to test the MRI images, manually. Nowadays, the advancement of Computer-assisted Diagnosis (CAD), machine learning, and deep learning in specific allow the radiologist to more reliably identify brain tumors. The traditional machine learning methods used to tackle this problem require a handcrafted feature for classification purposes. Whereas deep learning methods can be designed in a way to not require any handcrafted feature extraction while achieving accurate classification results. This paper proposes two deep learning models to identify both binary (normal and abnormal) and multiclass (meningioma, glioma, and pituitary) brain tumors. We use two publicly available datasets that include 3064 and 152 MRI images, respectively.

b) Inference

This research introduces two deep learning models for identifying brain abnormalities as well as classifying different tumor grades, including meningioma, glioma, and pituitary. The "proposed 23-layer CNN" architecture is designed to work with a relatively large volume of image data, whereas the "Fine-tuned CNN with VGG16" architecture is designed for a limited amount of image data. A comprehensive data augmentation technique is also conducted to enhance the "Fine-tuned CNN with VGG16" model's performance. Our experimental results demonstrated that both models enhance the prediction performance of diagnosis of brain tumors. We achieved 97.8% and 100% prediction accuracy for dataset 1 and dataset 2, respectively outperforming previous studies found in the literature. Therefore, we believe that our proposed methods are outstanding candidates for brain tumor detection.

4.Alwakid G, Gouda W, Humayun M, Sama NU. Melanoma Detection Using Deep Learning-Based Classifications. Healthcare (Basel). 2022

a) Abstract

One of the most prevalent cancers worldwide is skin cancer, and it is becoming more common as the population ages. As a general rule, the earlier skin cancer can be diagnosed, the better. As a result of the success of deep learning (DL) algorithms in other industries, there has been a substantial increase in automated diagnosis systems in healthcare. This work proposes DL as a method for extracting a lesion zone with precision. First, the image is enhanced using Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) to improve the image's quality. Then, segmentation is used to segment Regions of Interest (ROI) from the full image. We employed data augmentation to rectify the data disparity. The image is then analyzed with a convolutional neural network (CNN) and a modified version of Resnet-50 to classify skin lesions. This analysis utilized an unequal sample of seven kinds of skin cancer from the HAM10000 dataset.

b) Inference

Researchers devised a method for promptly and accurately diagnosing seven different types of cancer by analyzing skin lesions. The suggested method uses image-enhancing techniques to brighten the lesion image and remove noise. Preprocessed lesion medical imaging was used to train CNN and modified Resnet-50 to avoid overfitting and to boost the overall competence of the suggested DL approaches. The proposed approach was challenged using a dataset of lesion images known as the HAM10000 dataset. When employing CNN and a modified Resnet-50, the conception model had an accuracy rate of 85.3 percent and 85.98 percent $\approx$ 86 percent, respectively, comparable to the accuracy rate of professional dermatologists, as proposed. In addition, the research's originality and contribution lie in its use of ESRGAN as a pre-processing step with the various models (designed CNN and modified Resnet50) and in its contribution to the field. Compared to the pre-trained Model, our new Model performs similarly. Current models are outperformed by the proposed system, as demonstrated by comparison studies.

Chapter 3: Requirement Gathering for the Proposed System

3.1 Functional Requirements

1. Brain Tumor Classification:

a. Image Input: The app should allow users to upload or capture images of brain scans (e.g., MRI, CT scans) for analysis.

b. Image Processing: Implement algorithms for processing and analyzing brain scan images to detect and classify potential tumors.

c. Classification Accuracy: Ensure high accuracy in tumor classification through advanced image analysis techniques and machine learning algorithms.

d. Diagnostic Report: Generate detailed diagnostic reports indicating the presence, location, and characteristics of detected brain tumors.

e. Recommendation System: Provide personalized recommendations for further diagnostic procedures or consultations with healthcare professionals based on the classification results.

2. Skin Cancer Classification:

a. Image Input: Enable users to upload or capture images of skin lesions, moles, or affected areas for examination.

b. Image Analysis: Develop algorithms for analyzing skin images to identify suspicious lesions and classify them into different types of skin cancer (e.g., melanoma, basal cell carcinoma, squamous cell carcinoma).

c. Risk Assessment: Assess the risk level associated with detected skin lesions and provide corresponding recommendations for follow-up actions.

d. Educational Resources: Offer educational materials and resources to users, including information on skin cancer prevention, self-examination techniques, and warning signs to watch for.

3. Doctor Finder:

a. Location-Based Search: Implement a location-based search feature to help users find nearby healthcare professionals, including doctors specializing in neurology (for brain tumor consultations) and dermatology (for skin cancer consultations).

b. Specialization Filters: Allow users to filter search results based on specific medical specialties relevant to brain and skin cancer diagnosis and treatment.

c. Doctor Profiles: Display detailed profiles of healthcare providers, including their credentials, areas of expertise, clinic/hospital affiliations, and patient reviews.

d. Appointment Scheduling: Enable users to schedule appointments directly through the app, facilitating seamless communication and coordination with healthcare providers.

e. Integration with Maps: Integrate with mapping services to provide directions to the selected healthcare provider's location, enhancing user convenience and accessibility.

3.2 Non-Functional Requirements

1. Performance:

a. Response Time: The app should have fast response times for image processing and analysis, ensuring minimal delay in providing diagnostic results.

b. Scalability: Design the app to handle a large number of concurrent users and accommodate potential increases in user base without significant degradation in performance.

c. Reliability: Ensure high reliability and uptime of the app, minimizing the occurrence of downtime or service interruptions to maintain user trust and satisfaction.

2. Security:

a. Data Encryption: Implement strong encryption mechanisms to protect sensitive user data, including medical images, personal information, and communication with healthcare providers.

b. Authentication Mechanism: Employ secure authentication protocols to verify the identity of users and prevent unauthorized access to their accounts and medical information.

c. Secure Transmission: Ensure secure transmission of data between the app and external servers, utilizing encryption and secure communication protocols to prevent interception or tampering.

3. Privacy:

a. Data Privacy: Adhere to strict privacy standards and regulations (e.g., HIPAA) to safeguard the confidentiality and privacy of user health information and medical records.
b. Anonymization: Implement techniques to anonymize user data where applicable, minimizing the risk of re-identification and protecting user privacy.
c. Consent Management: Provide users with clear information about data collection practices and obtain explicit consent for the use and sharing of their personal and medical data.

4. Usability:

a. User Interface Design: Design an intuitive and visually appealing user interface (UI) with clear navigation, consistent layout, and user-friendly interactions to enhance usability.
b. Accessibility: Ensure accessibility for users with disabilities by adhering to accessibility standards (e.g., WCAG) and incorporating features such as keyboard navigation, screen reader compatibility, and adjustable contrast settings.
c. Multilingual Support: Provide support for multiple languages to accommodate users from diverse linguistic backgrounds, enhancing inclusivity and usability for a broader audience.

5. Compatibility:

a. Cross-Platform Compatibility: Develop the app to be compatible with a wide range of devices and operating systems (e.g., iOS, Android) to maximize accessibility and reach.
b. Browser Compatibility: Ensure compatibility with popular web browsers to enable users to access the app via web browsers on various devices, including desktop computers and tablets.
c. Integration Compatibility: Facilitate seamless integration with external systems and services, such as mapping services for location-based features and healthcare provider databases for doctor finder functionality.

6. Compliance:

a. Regulatory Compliance: Ensure compliance with relevant regulations and standards governing healthcare apps, including data protection laws (e.g., GDPR, HIPAA) and medical device regulations (e.g., FDA guidelines).

b. Ethical Guidelines: Adhere to ethical guidelines and principles in the development and deployment of the app, including principles of beneficence, non-maleficence, and respect for user autonomy.
c. Quality Assurance: Implement rigorous quality assurance processes to verify compliance with regulatory requirements and ensure the safety, effectiveness, and reliability of the app.

3.3.Hardware, Software , Technology and tools utilized

Hardware:

- Processor: Intel i3 or AMD equivalent
- Disk Space: 4GB
- RAM: 8GB
- GPU: Nvidia GPU

Software:

- Google Colab: Utilized for developing and running machine learning algorithms and image processing tasks, leveraging its compatibility with Python and access to GPU resources for accelerated computation.
- Android Studio: Used as the primary integrated development environment (IDE) for Android app development, providing tools for designing, coding, and testing mobile applications.
- Java Development Kit (JDK): Required for Android app development, providing the Java runtime environment and tools for compiling and running Java code within Android Studio.
- XML (Extensible Markup Language): Employed for designing user interfaces (UI) and layouts within Android Studio, facilitating the creation of visually appealing and responsive UI components.

- SQLite Database: Integrated into the Android app for storing and managing structured data locally on users' devices, including user preferences, diagnostic results, and healthcare provider information.
- Java: Utilized as the primary programming language for Android app development, enabling the implementation of app logic, user interface interactions, and backend functionality.
- Python: Employed for developing machine learning models, image processing algorithms, and backend server scripts within Google Colab, leveraging its extensive libraries for data analysis and machine learning tasks.
- Android SDK (Software Development Kit): Integrated with Android Studio to access a comprehensive set of development tools, libraries, and APIs for building feature-rich Android applications.
- TensorFlow: Utilized for developing and deploying machine learning models within Google Colab, enabling tasks such as image classification, object detection, and neural network training.
- OpenCV (Open Source Computer Vision Library): Incorporated into both Google Colab and Android Studio for implementing image processing algorithms and computer vision tasks, such as image enhancement, feature extraction, and pattern recognition.

Chapter 4: Proposed Design

4.1 Block diagram of the system

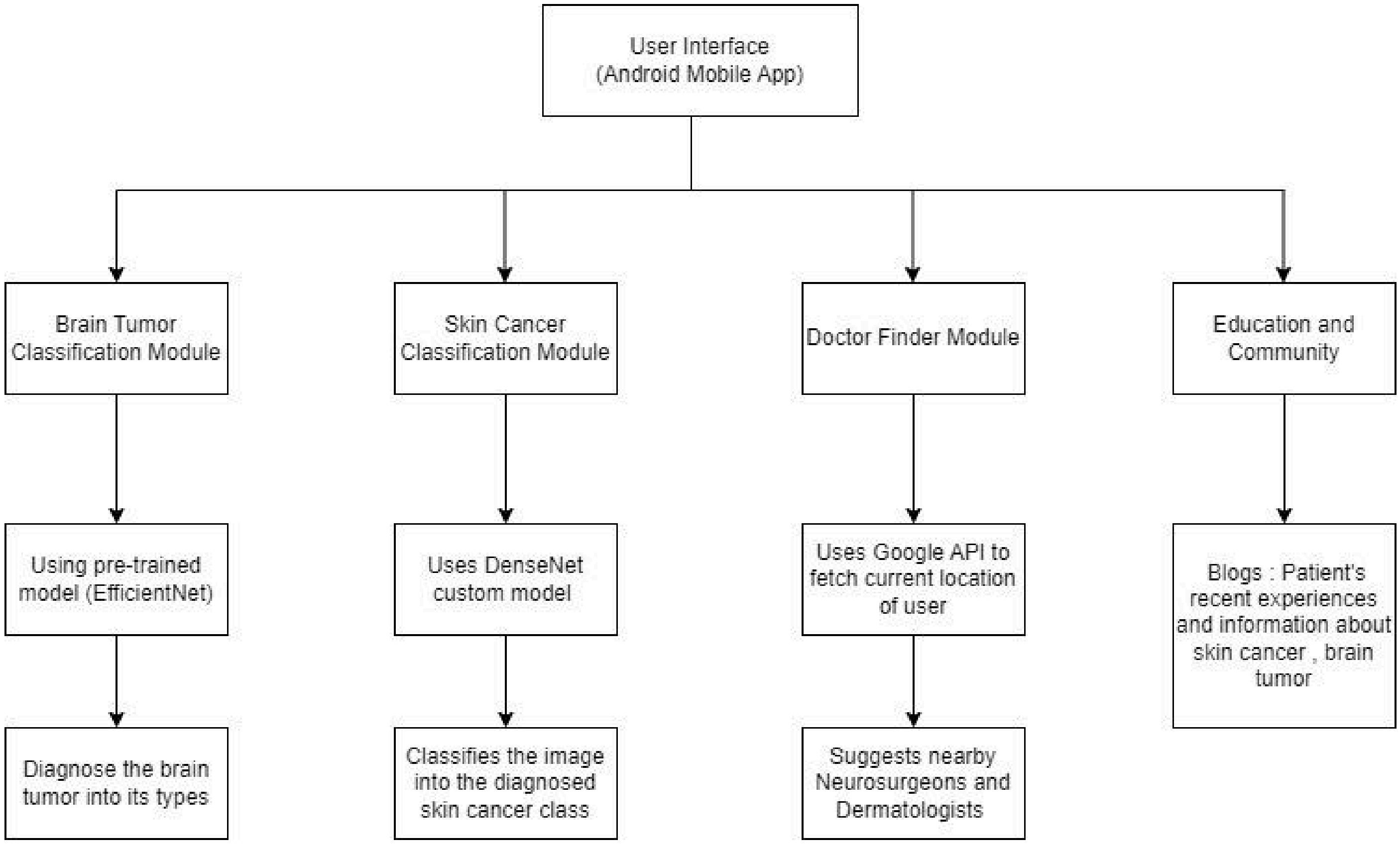


Fig 4.1.1 : Block diagram

4.2 Modular design of the system

Fig 4.2.1 : Modular Diagram

4.3 Project Scheduling & Tracking using Timeline / Gantt Chart

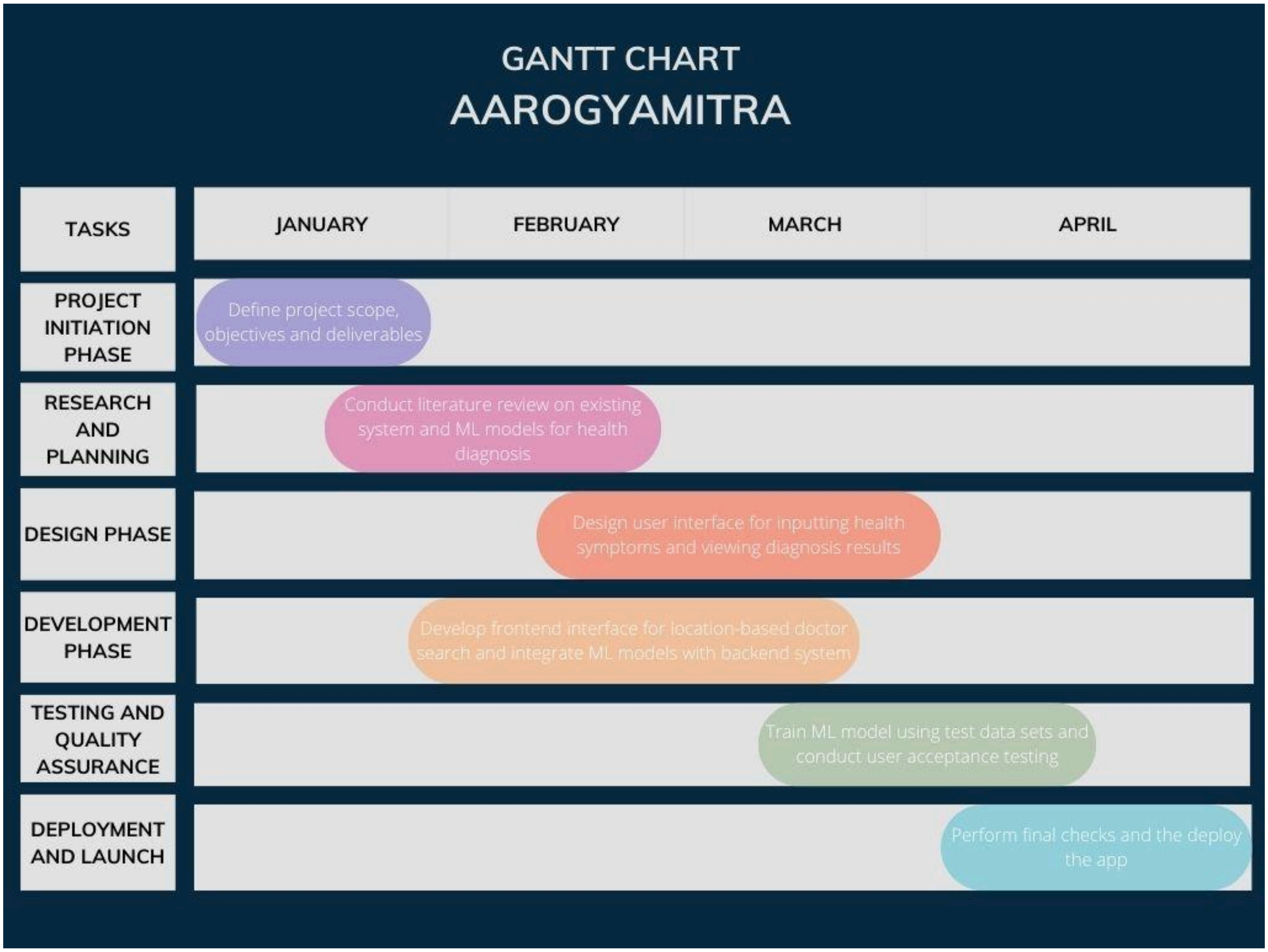


Fig 4.3.1 : Gantt Chart

Chapter 5: Implementation of the Proposed System

5.1. Methodology employed for development

Leveraging the power of advanced machine learning algorithms for skin cancer and brain tumor detection, the application seeks to improve patient outcomes and empower individuals to take control of their health journey. A flowchart of the basic steps adopted for the machine learning model is shown in Fig 1. First, data cleaning is performed to convert the raw data into a usable form. After data cleaning, data analysis is done to determine the importance of features. In data analysis, the features are identified, and the data are converted into a form on which machine learning models can be applied. These steps are used for each of the model predictions: (a)Brain Tumor (b) Melanoma – Skin Cancer.

(a) In this section, firstly we present a methodology for brain tumor classification using transfer learning with deep learning techniques applied to MRI images. Our approach involves several key steps to build and train a classification model. Firstly, we prepare the dataset comprising MRI images representing different brain tumor types, including glioma, meningioma, pituitary tumor, and tumor-free samples as shown in Fig 2. The images are preprocessed by resizing them to a standardized dimension using OpenCV, and corresponding labels are assigned for each tumor type. This entire dataset is then split into training and test sets as shown in Fig 3. Subsequently, we employ transfer learning with the EfficientNetB0 model, leveraging its pre-trained weights from the ImageNet dataset. By excluding the top layer, we customize the model for our classification task, allowing it to serve as a feature extractor to learn relevant features from the MRI images.

To design the model architecture, we add additional layers on top of the pre-trained EfficientNetB0 model. This includes a GlobalAveragePooling2D layer to reduce spatial dimensions, a Dropout layer to mitigate overfitting, and a Dense layer with softmax activation for classification. The model is then compiled with appropriate loss function, optimizer, and evaluation metric. Training is conducted using the compiled model and prepared dataset, with validation data used to monitor performance. We employ various callbacks such as TensorBoard, ModelCheckpoint, and ReduceLROnPlateau to track training progress, save the best model, and dynamically adjust learning rate.

After training, the model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. Visualization tools such as TensorBoard aid in understanding model behavior and identifying potential issues like overfitting. Our methodology provides a systematic approach to building and training a classification model for brain tumor classification, leveraging transfer learning and deep learning techniques to achieve accurate and reliable results.

(b) Automated classification of skin lesions using images is a challenging task owing to the fine-grained variability in the appearance of skin lesions. The methodology encompasses several key steps aimed at effectively analyzing skin cancer image data and developing a robust classification model. Firstly, the process begins with acquiring high-quality skin cancer image data from reliable sources like Kaggle. The pictures have all been resized to low resolution (224x224x3) RGB. It has 2 different classes of skin cancer which are listed below :

1. Benign 2. Malignant

Essential preprocessing steps involve importing necessary libraries such as NumPy, Matplotlib, Pandas, and TensorFlow/Keras for data manipulation and analysis. The dataset, typically stored in a CSV file, is loaded using Pandas, allowing access to pixel data and corresponding labels. Subsequent data exploration includes visualizing data distribution to identify any class imbalances, which are crucial for subsequent analyses. Addressing observed class imbalances, data augmentation techniques are applied. Leveraging the ImageDataGenerator from Keras, new images are generated through transformations like rotation, shifting, and flipping. Additionally, data duplication is implemented for minority classes to balance the dataset, with random optimal values selected to centralize the augmented data.

Training of neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available dataset of dermatoscopic images.This problem is tackled by using the HAM10000 ("Human Against Machine with 10000 training images") dataset. This dataset has collected dermatoscopic images from different populations, acquired and stored by different modalities. The final dataset consists of 10015 dermatoscopic images which can serve as a training set for academic machine learning purposes. Cases include a representative collection of all important diagnostic categories in the realm of pigmented lesions:

Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratosis, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage,vasc). More than 50% of lesions are confirmed through histopathology (histo), the ground truth for the rest of the cases is either follow-up examination (follow_up), expert consensus (consensus), or confirmation by in-vivo confocal microscopy (confocal). The dataset includes lesions with multiple images, which can be tracked by the lesion_id-column within the HAM10000_metadata file.

After getting a dataset that has been resized, the data is then cleaned by removing data that is not good to use. Then the dataset is divided into training data, validation data and test data with 80:10:10 division

Deep Residual Network (ResNet) is an Artificial Neural Network that is created with the aim of overcoming the problem of lower accuracy when creating a plain ANN with a deeper layer than a shallower ANN. In other words, the purpose of the Deep Residual Network is to make ANN with deeper layers with high accuracy. The concept of the Deep Residual Network is to make ANN that can update the weight to a shallower layer (reduce degradation gradient). The concept is implemented using a "shortcut connection".

We applied transfer learning for skin lesion classification by slightly modifying architecture and fine-tuning weights of the ResNet50 models pre-trained on the ImageNet dataset. The modification included the use of global average pooling instead of average pooling. Hyper-parameters are important when they directly influence the attitudes of the system, since fine-tuned hyperparameters have a significant effect on the model's output. To train 10 epochs , we have used Adam optimizer, and for the batch size of 32, we set a learning rate of 0.0001.Furthermore, The categorical cross entropy loss function given below calculates the loss of class probability predicted by the soft max function. And finally measure the probability of each category.

5.2 Datasets source and utilization

Skin Cancer dataset: The final dataset consists of 10015 dermatoscopic images which can serve as a training set for academic machine learning purposes. Cases include a representative collection of all important diagnostic categories in the realm of pigmented lesions: Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc).

More than 50% of lesions are confirmed through histopathology (histo), the ground truth for the rest of the cases is either follow-up examination (follow_up), expert consensus (consensus), or confirmation by in-vivo confocal microscopy (confocal). The dataset includes lesions with multiple images, which can be tracked by the lesion_id-column within the HAM10000_metadata file.

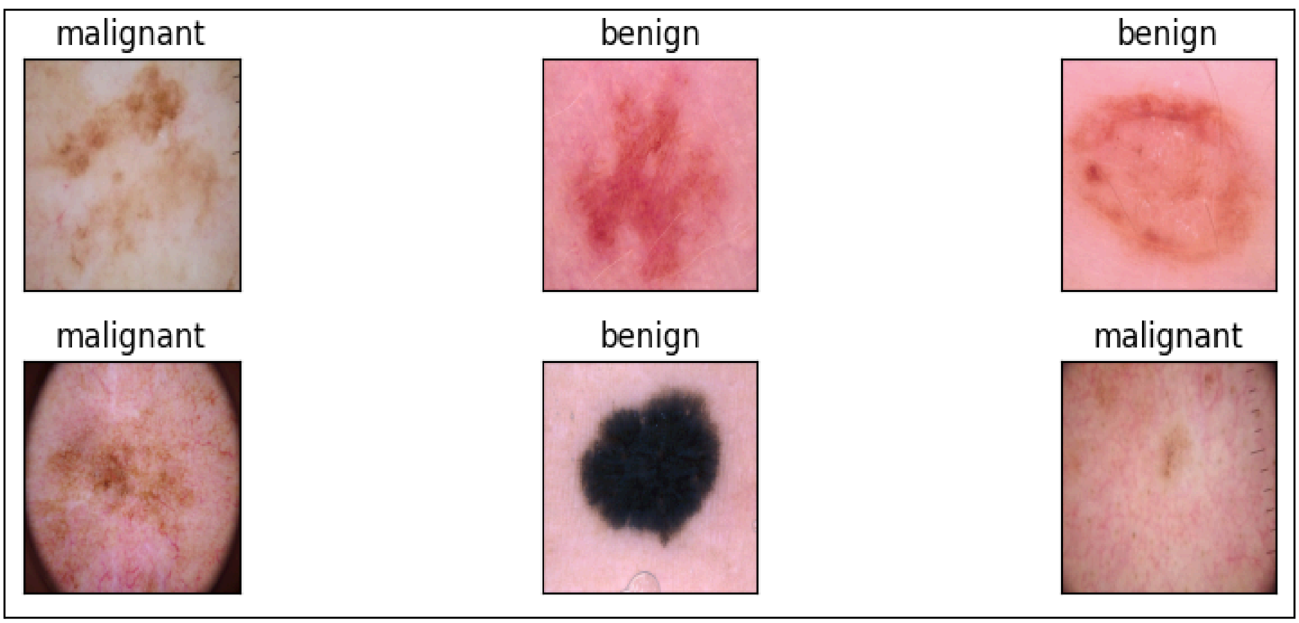


Fig 5.2.1 : Skin Cancer – Melanoma Dataset

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

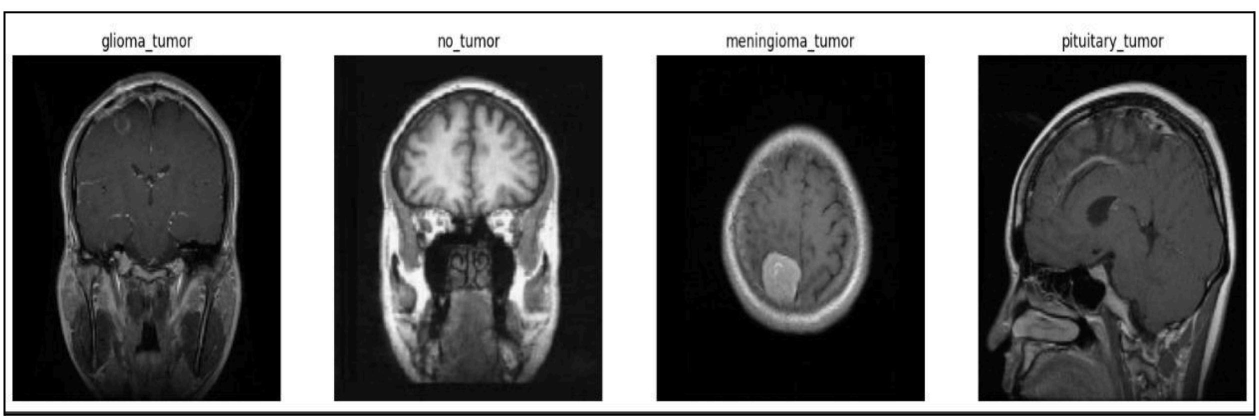
Table 5.2.2 : Skin Cancer Dataset Metadata

Brain Tumor Dataset:

The data required is MRI data which is gathered from the internet. The data is cleaned for any outliers. The data set is uploaded on Kaggle.com for use in ML community and other enthusiasts. The images are already split into Training and Testing folders.

Each folder has more four subfolders. These folders have MRIs of respective tumor classes.

URL : www.kaggle.com/sartajbhuvaji/brain-tumor-classification-mri



Chapter 6: Testing of the Proposed System

6.1 . Introduction to testing

Testing the Aarogyamitra Health Diagnosis App is crucial to ensuring its reliability, accuracy, and user satisfaction. The testing process encompasses various methodologies, including functional, integration, user acceptance, performance, and security testing. Functional testing verifies individual features such as image classification and doctor finder functionality, while integration testing ensures seamless interaction between different modules. User acceptance testing involves real users to assess usability and satisfaction. Performance testing evaluates responsiveness and scalability, while security testing identifies vulnerabilities. Testing scenarios include image processing, diagnosis accuracy, and compatibility across devices. Utilizing testing tools and environments, the goal is to validate compliance with functional requirements, address potential issues, and deliver a seamless user experience, ultimately empowering users with accessible and reliable healthcare solutions.

6.2. Types of tests Considered

Functional Testing: This testing validates the app's key features and functionalities, including:

- Image classification: Ensuring accurate classification of brain tumor and skin cancer images.
- Diagnostic report generation: Verifying the generation of detailed and informative diagnostic reports based on classification results.
- Doctor finder functionality: Testing the ability to search for nearby healthcare providers based on location and specialization.

Integration Testing: Integration testing ensures smooth interaction and communication between different modules of the app, such as:

- Backend services: Verifying seamless communication between backend servers handling data processing and storage.
- Machine learning algorithms: Ensuring proper integration and functioning of algorithms for image classification.
- User interface components: Testing the integration of backend functionalities with the user interface for a cohesive user experience.

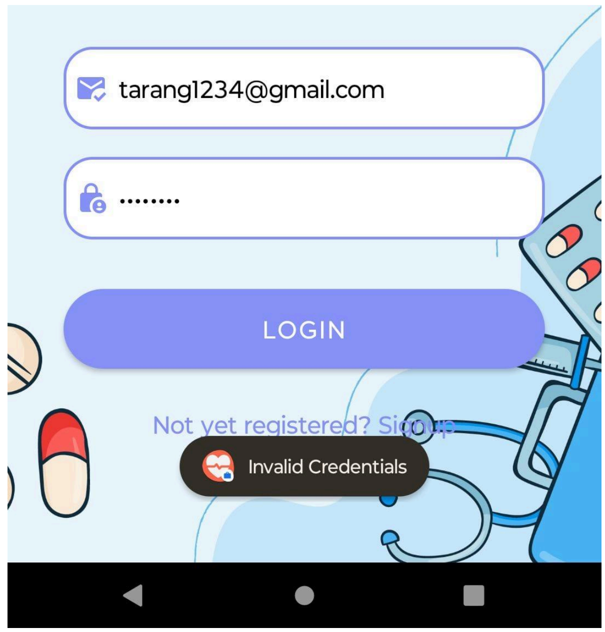
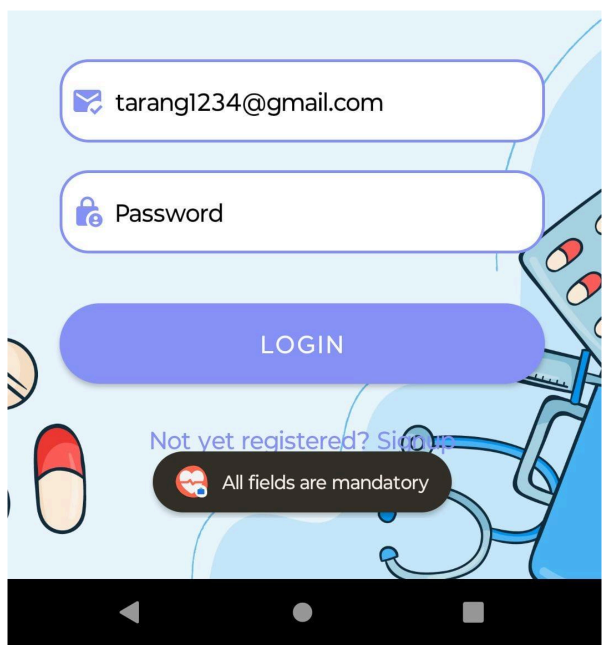
User Acceptance Testing (UAT): User acceptance testing involves real users to assess the app's usability and overall satisfaction, focusing on:

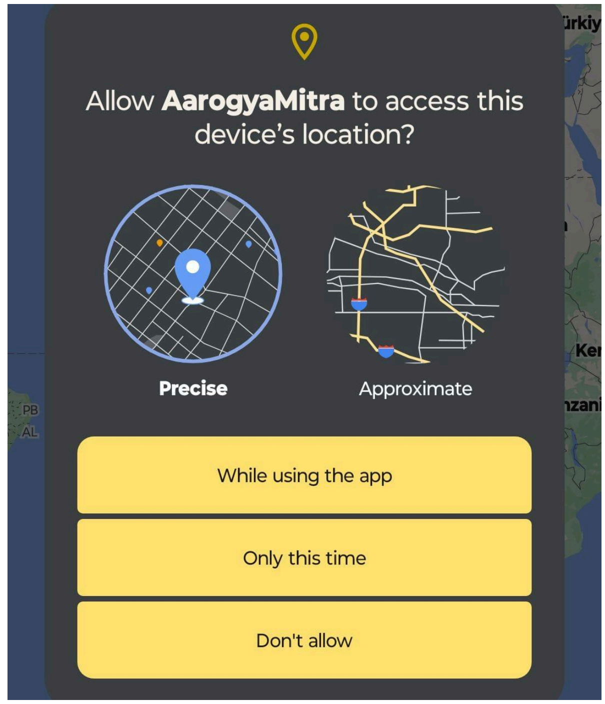
- User interface design: Evaluating the intuitiveness and accessibility of the app's interface for diverse user demographics.
- Usability: Gathering feedback on ease of navigation, clarity of instructions, and overall user experience.
- Overall satisfaction: Gauging user satisfaction with the app's performance and utility in meeting their healthcare needs.

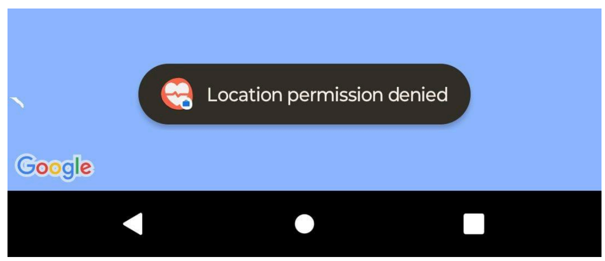
Performance Testing: Performance testing evaluates the app's responsiveness, scalability, and resource utilization, including:

- Responsiveness: Assessing the app's speed and responsiveness in processing image uploads, generating diagnostic reports, and displaying search results.
- Scalability: Testing the app's ability to handle increasing user load and data volume without compromising performance.

6.3 Various test case scenarios considered

	Test Cases
Case 1:The input field for 'username' should only accept valid email.	
Case 2:All required fields should be filled	

<table>
<tr>
<td>Case 3:Location should be turned on</td>
<td>




</td>
</tr>
</table>

Chapter 7: Results and Discussion

7.1. Screenshots of User Interface (UI)

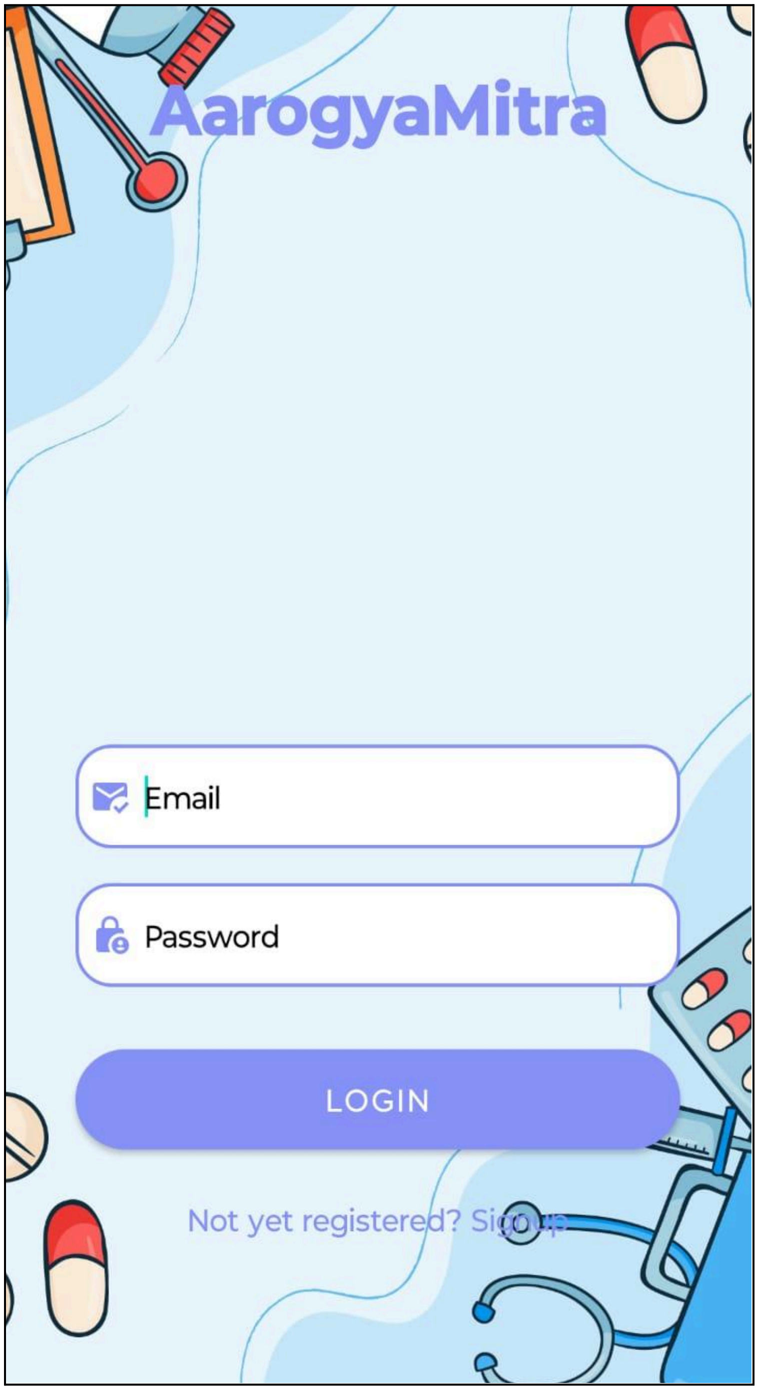


Fig 7.1.1 : Login Page

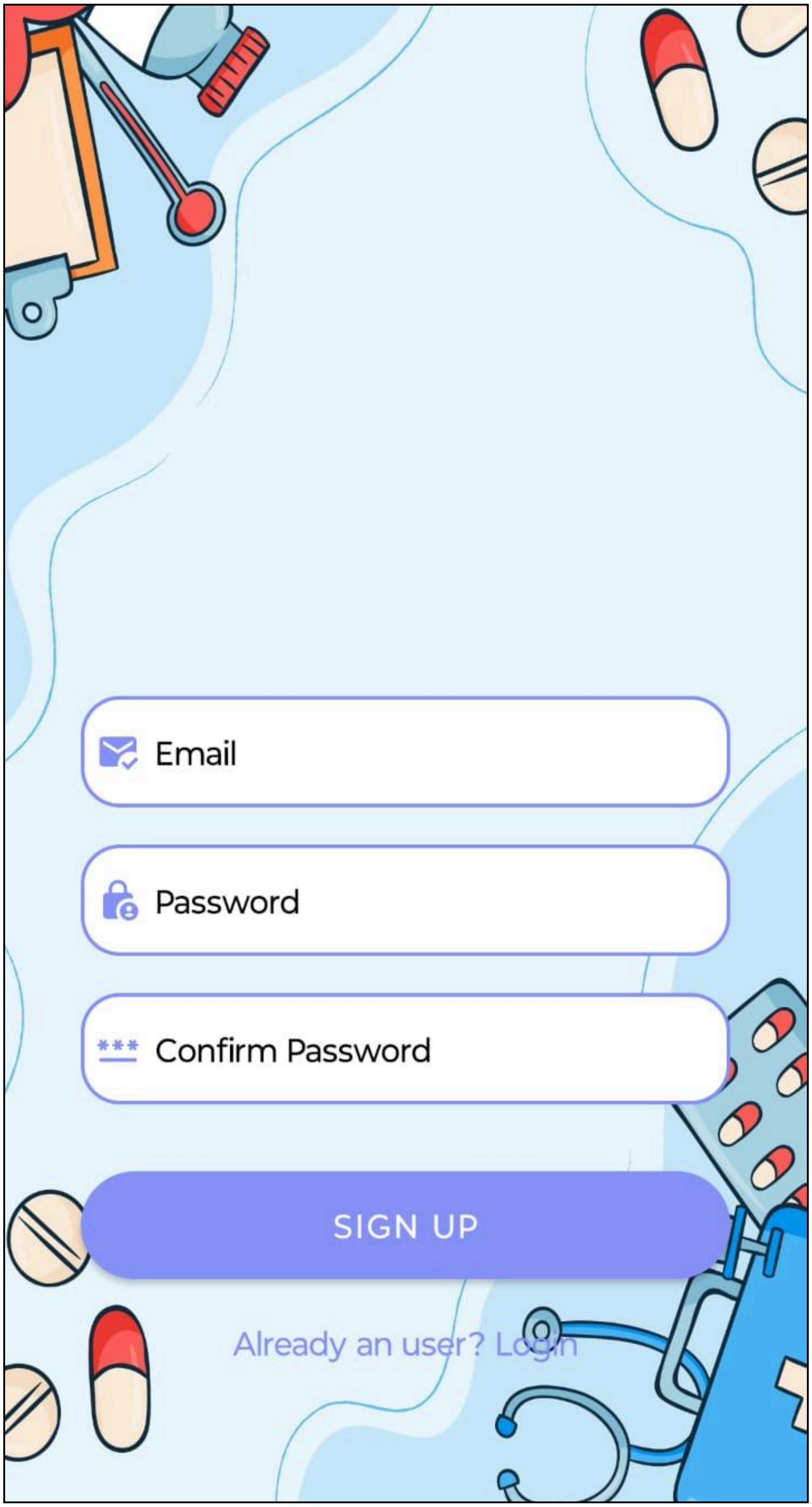
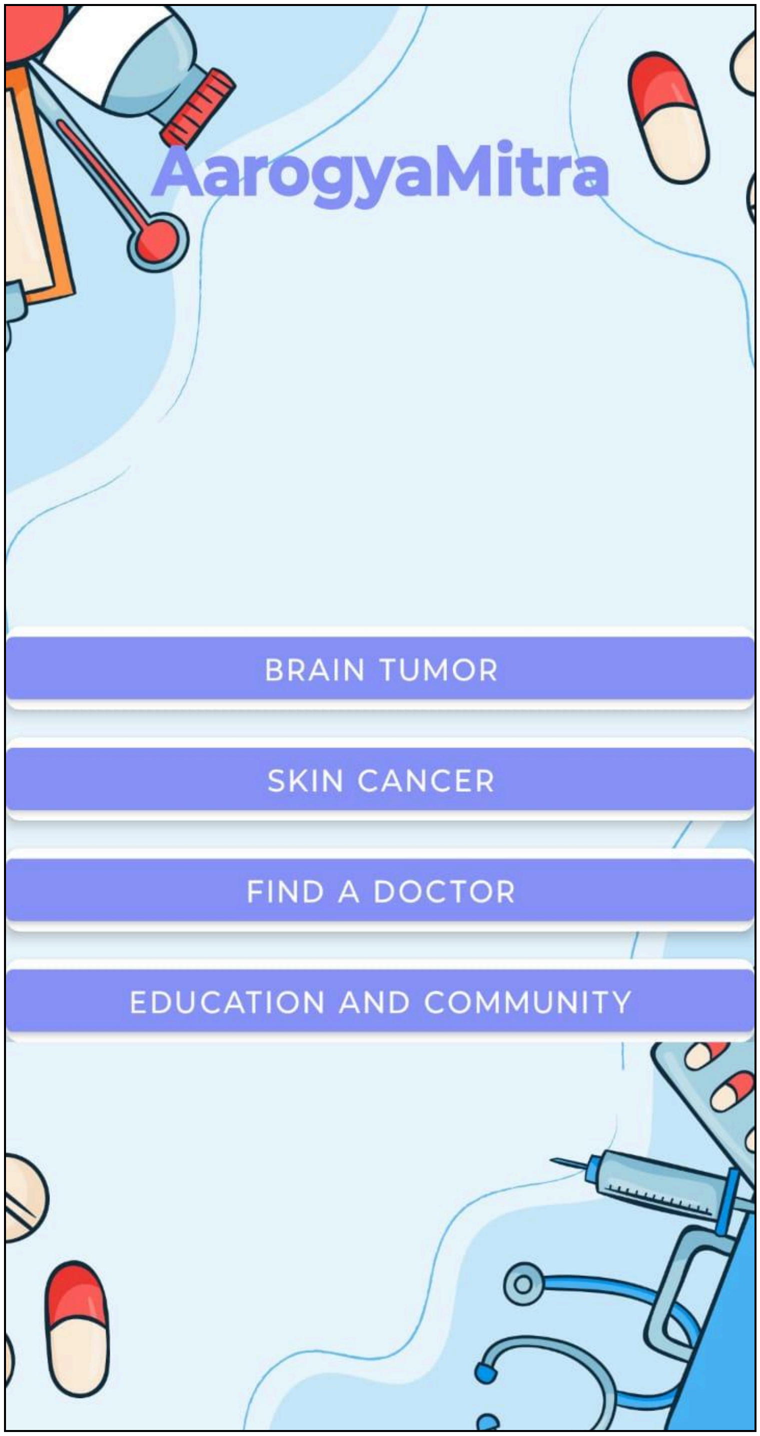


Fig 7.1.2 : Signup Page



7.1.3 : Home page

Fig 7.1.4 : Brain tumor detection page

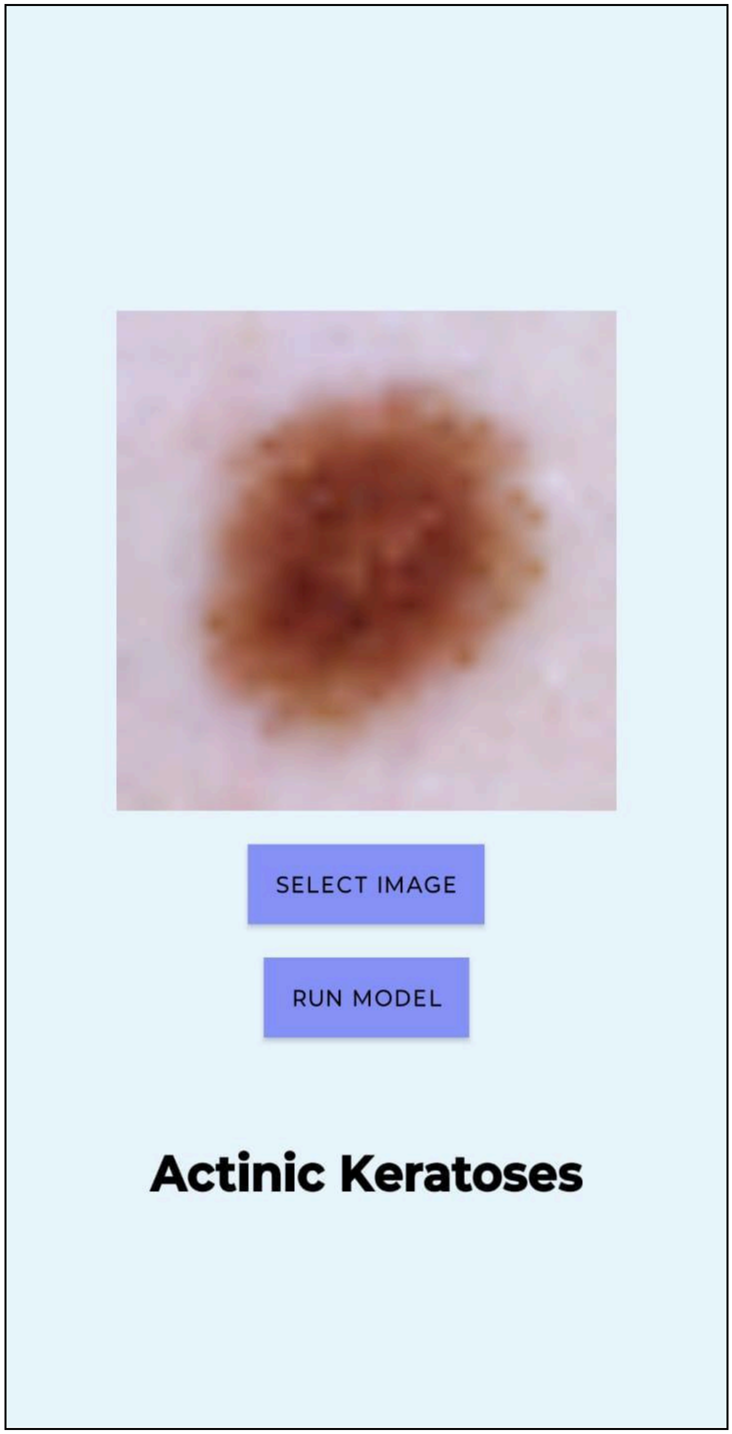


Fig 7.1.5 : Skin cancer detection page

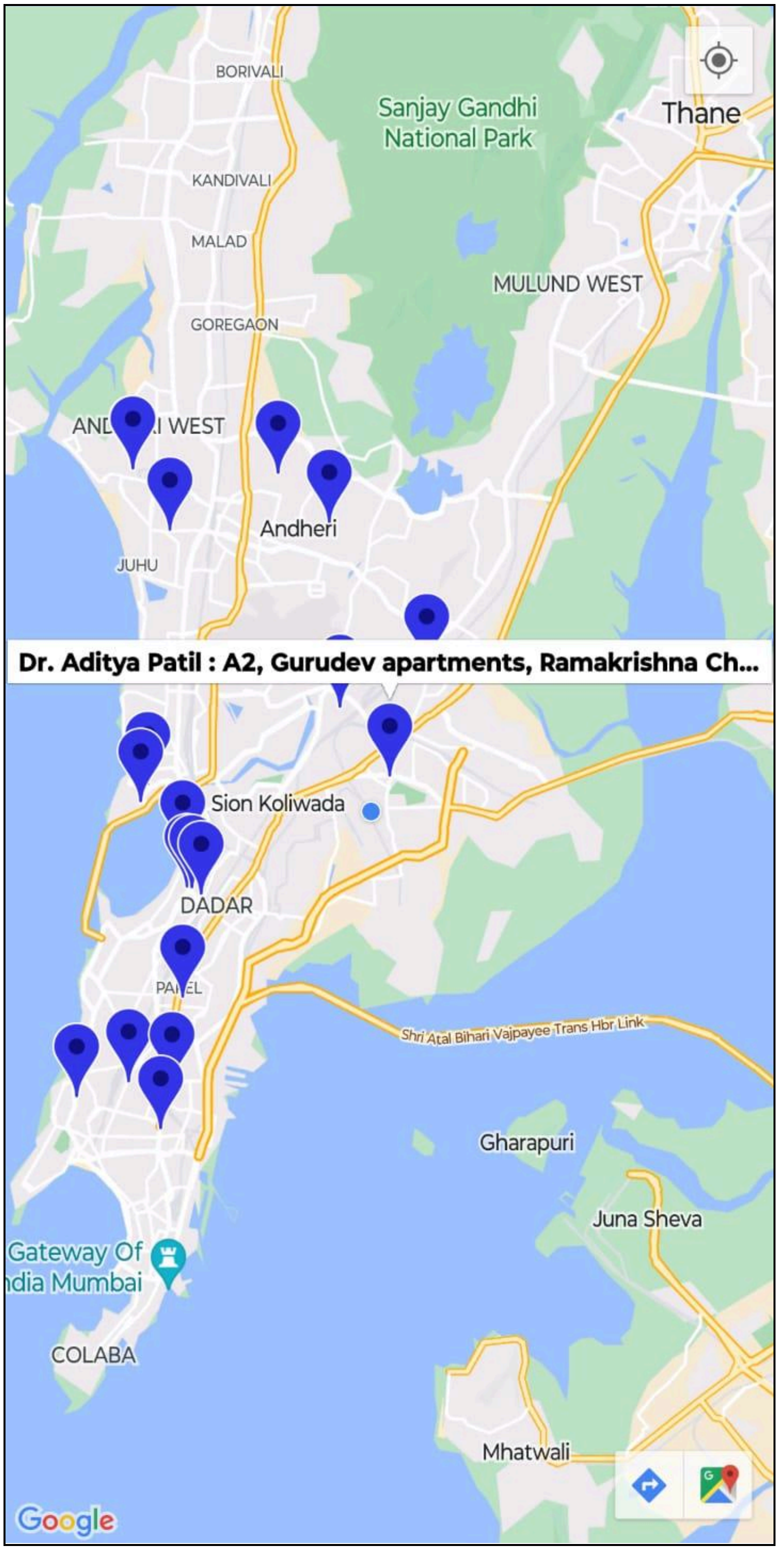


Fig 7.1.6 : Finding doctors based on detected location

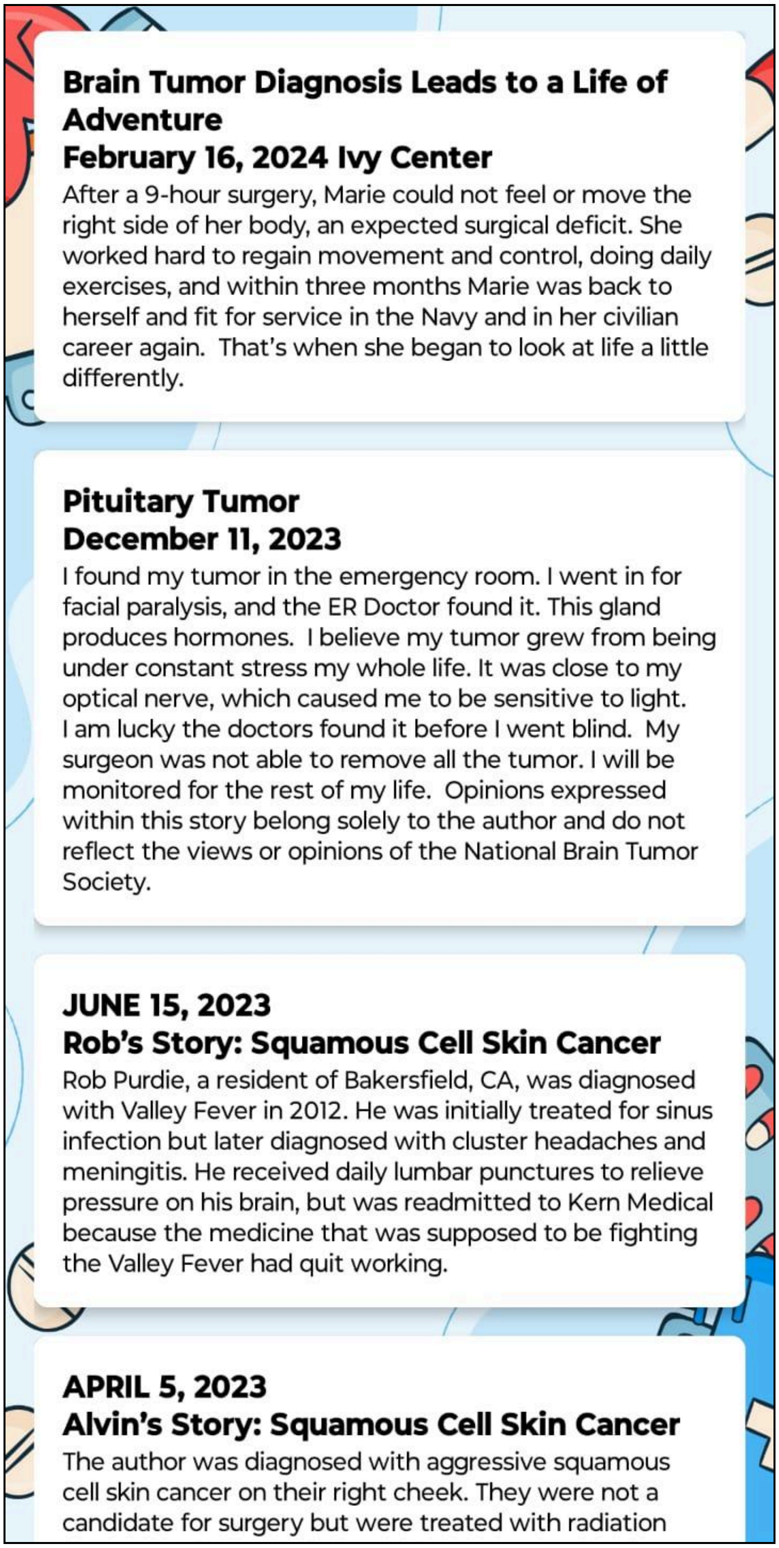


Fig 7.1.7 : Education and community blogs

Chapter 8: Conclusion

8.1 Limitations

Accuracy of Diagnosis:

Although the app leverages advanced machine learning algorithms for skin cancer and brain tumor classification, the accuracy of diagnosis may not be 100%. Users should be aware that the app serves as a supplementary tool and should not replace professional medical diagnosis and advice.

Data Availability and Diversity:

The accuracy of the app's classification models heavily relies on the availability and diversity of training data. Limitations in the quantity or diversity of data may affect the model's ability to accurately classify certain types of skin lesions or brain tumors.

Limited Scope of Diagnosis:

The app may not cover all possible skin conditions or brain tumor types. It focuses primarily on common types of skin cancer and brain tumors, potentially overlooking rarer or more complex conditions that require specialized diagnosis and treatment.

Reliance on User-Provided Information:

The accuracy of the app's diagnosis depends on the quality and completeness of the information provided by the user, such as image quality and accompanying symptoms. Inaccurate or insufficient data may lead to incorrect diagnoses or recommendations.

Network Connectivity Requirement:

Some features of the app, such as accessing backend services for image processing or doctor finder functionality, may require a stable internet connection. Users in areas with limited connectivity may experience difficulties in accessing these features.

Privacy and Security Concerns:

As the app involves the exchange of sensitive medical information, ensuring robust privacy and security measures is crucial. However, despite implementing encryption and other security protocols, there may still be inherent risks associated with data breaches or unauthorized access.

Device Compatibility and Performance:

The app's performance and usability may vary depending on the user's device specifications, operating system version, and available resources. Older or low-end devices may experience slower performance or compatibility issues.

Regulatory Compliance:

Ensuring compliance with healthcare regulations and standards, such as HIPAA (Health Insurance Portability and Accountability Act), is essential but challenging. Changes in regulations or legal requirements may necessitate updates to the app's functionality or policies.

8.2 Conclusion

In conclusion, the Aarogyamitra Health Diagnosis App represents a significant advancement in leveraging technology to empower individuals in managing their health. By incorporating advanced machine learning algorithms for skin cancer and brain tumor classification, along with a convenient doctor finder feature, the app aims to provide users with accessible and reliable healthcare solutions.

Throughout the development and testing process, various methodologies, including functional testing, integration testing, user acceptance testing, and performance testing, have been employed to ensure the app's reliability, accuracy, and usability. However, it's crucial to acknowledge the app's limitations, such as potential inaccuracies in diagnosis, data availability constraints, and privacy concerns.

Despite these challenges, the app holds promise in supplementing traditional healthcare practices, providing users with valuable insights and resources for early detection and management of health conditions. Moving forward, continuous improvements, user feedback integration, and adherence to regulatory compliance will be essential for enhancing the app's effectiveness and user satisfaction.

In essence, the Aarogyamitra Health Diagnosis App represents a step towards democratizing healthcare access and empowering individuals to take proactive steps towards their well-being. Through innovation, collaboration, and a commitment to user-centric design, the app strives to make a meaningful impact on public health and improve patient outcomes in the digital age.

8.3 Future Scope

Enhanced Diagnosis Accuracy:

Continuously improving the accuracy of skin cancer and brain tumor classification algorithms through ongoing research and development. This may involve collecting more diverse and comprehensive datasets, exploring new machine learning techniques, and collaborating with medical professionals to refine diagnostic criteria.

Expansion of Diagnostic Capabilities:

Broadening the scope of the app to cover a wider range of health conditions beyond skin cancer and brain tumors. This could include incorporating algorithms for detecting other types of cancer, chronic diseases, or infectious conditions, thereby increasing the app's utility and relevance to a larger population.

Integration of Telemedicine Features:

Introducing telemedicine functionalities within the app to facilitate remote consultations and follow-up appointments with healthcare providers. This could include real-time video consultations, secure messaging, and electronic health record (EHR) integration, enabling seamless communication and coordination of care between patients and providers.

Personalized Health Recommendations:

Implementing personalized health recommendations and interventions based on users' medical history, lifestyle factors, and genetic predispositions. This could involve leveraging artificial intelligence and data analytics to generate tailored health insights, preventive strategies, and treatment plans that align with individual preferences and needs.

Expansion to Wearable Devices:

Integrating with wearable devices and health tracking technologies to provide continuous monitoring of vital signs, activity levels, and physiological parameters. This would enable the app to offer proactive health monitoring, early detection of health issues, and personalized feedback for lifestyle modifications.

Global Outreach and Localization:

Expanding the app's availability to international markets and adapting its content and features to cater to diverse cultural and linguistic preferences. This may involve translating the app into multiple languages, incorporating region-specific health guidelines and resources, and partnering with local healthcare providers and organizations.

Enhanced Security and Privacy Measures:

Strengthening the app's security protocols and privacy safeguards to protect users' sensitive health information from cyber threats and unauthorized access. This could include implementing advanced encryption techniques, adopting secure authentication mechanisms, and ensuring compliance with stringent data protection regulations.

Longitudinal Health Monitoring:

Developing mechanisms for longitudinal health monitoring and trend analysis, allowing users to track changes in their health status over time and receive proactive alerts for potential health risks or deviations from normal patterns.

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2. 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

3. 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

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Appendix

1] Paper I Details:

a. Paper I:

Abstract—Many researchers have recently used a variety of supervised learning techniques to create a range of automated diagnosis models. Early disease detection could reduce the number of people who die from these conditions. This research uses machine learning models to develop an effective automated disease diagnostic algorithm. We have chosen two serious illnesses, including melanoma and brain tumors, for this essay. The suggested model involves entering the data into an Android app, utilizing a pre-trained machine learning model that was trained on the same dataset and deployed on Firebase for analysis in a real-time database, and ultimately displaying the illness detection result in the Android app. The prediction computation is done using logistic regression. Determining the risk of diabetes, heart disease, and coronavirus can be aided by early detection. A comparative investigation shows that the suggested model can assist medical professionals in providing timely prescriptions for therapy.

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 paper aims to outline the key components of the application, particularly highlighting the utilization of advanced machine learning models for skin cancer and brain tumor detection and classification. Through the integration of advanced machine learning algorithms, the application offers users the ability to upload skin images for the diagnosis of various types of skin cancer and brain MRI top view scans for the identification of different types of brain tumors. By providing timely and accurate diagnostic assessments, the application aims to facilitate early detection and intervention, ultimately improving patient outcomes. These machine learning models have been trained on large datasets of annotated images, enabling them to accurately identify and classify abnormalities indicative of skin cancer and brain tumors with high precision and reliability.

For skin cancer detection, the machine learning model is trained on a dataset comprising images of benign and malignant skin lesions, including melanoma. The model not only diagnoses the presence of skin cancer but also classifies the detected lesions into benign, malignant, or no cancerous growth. Similarly, for brain tumor detection, the machine learning model is trained on MRI images depicting different types of brain tumors, including glioma tumor, meningioma tumor, pituitary tumor, and normal brain scans. The model is capable of accurately identifying and classifying these tumors, as well as detecting cases where no tumor is present. The main contributions are as follows:

1. An efficient automated disease diagnosis model is designed using the machine learning models.
2. Two critical diseases are selected such as brain tumor and melanoma – skin cancer.
3. In the proposed model, the data are entered into an android app, the analysis is then performed in a real-time database using a pretrained machine learning model which was trained on the same dataset and deployed in firebase, and finally, the disease detection result is shown in the android app.
4. Logistic regression is used to carry out computation for prediction.

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.

I. Related work

Recent advancements in healthcare management systems have been marked by a surge in technological integration, particularly within the realm of medical record management. Bali, et al. [4] underscore the significance of detailed patient records in facilitating informed treatment decisions and personalized care adjustments, thereby enhancing patient outcomes. Sivasankari, et al. [4] introduce an Automated Health Care Management System leveraging big data technology, which not only enhances data quality through the conversion of free-text reports into structured formats but also streamlines healthcare operations for improved accessibility. Additionally, Kumar and Dutt [6] advocate for the implementation of machine learning models, specifically utilizing the random forest methodology, to organize acquired health data efficiently and accurately detect patient health information. Subramani, et al. [1] contribute to disease prediction with a stacking model incorporating various machine learning techniques, such as Gradient Boosted Decision Trees (GBDT), showcasing adaptability in predicting cardiovascular diseases. Furthermore, Zhang, et al. [2] underscore the transformative impact of AI and ML in cancer research, particularly in prognosis, prediction, and treatment selection, aiding in early detection and personalized treatment plans. Li, et al. [3] present a model-based reinforcement learning algorithm utilizing electronic health records (EHRs) to optimize treatment strategies, merging physiological and disease-specific factors through deep Q networks. In parallel, recent literature has witnessed significant strides in disease detection and diagnosis through the integration of machine learning and deep learning models with various medical imaging techniques.

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.

I. Methodology

Leveraging the power of advanced machine learning algorithms for skin cancer and brain tumor detection, the application seeks to improve patient outcomes and empower individuals to take control of their health journey. A flowchart of the basic steps adopted for the machine learning model is shown in Fig 1. First, data cleaning is performed to convert the raw data into a usable form. After data cleaning, data analysis is done to determine the importance of features. In data analysis, the features are identified, and the data are converted into a form on which machine learning models can be applied. These steps are used for each of the model predictions: (a)Brain Tumor (b) Melanoma – Skin Cancer.

(a) In this section, firstly we present a methodology for brain tumor classification using transfer learning with deep learning techniques applied to MRI images. Our approach involves several key steps to build and train a classification model. Firstly, we prepare the dataset comprising MRI images representing different brain tumor types, including glioma, meningioma, pituitary tumor, and tumor-free samples as shown in Fig 2. The images are preprocessed by resizing them to a standardized dimension using OpenCV, and corresponding labels are assigned for each tumor type. This entire dataset is then split into training and test sets as shown in Fig 3. Subsequently, we employ transfer learning with the EfficientNetB0 model, leveraging its pre-trained weights from the ImageNet dataset. By excluding the top layer, we customize the model for our classification task, allowing it to serve as a feature extractor to learn relevant features from the MRI images.

To design the model architecture, we add additional layers on top of the pre-trained EfficientNetB0 model. This includes a GlobalAveragePooling2D layer to reduce spatial dimensions, a Dropout layer to mitigate overfitting, and a Dense layer with softmax activation for classification. The model is then compiled with appropriate loss function, optimizer, and evaluation metric. Training is conducted using the compiled model and prepared dataset, with validation data used to monitor performance. We employ various callbacks such as TensorBoard, ModelCheckpoint, and ReduceLROnPlateau to track training progress, save the best model, and dynamically adjust learning rate.

After training, the model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score. Visualization tools such as TensorBoard aid in understanding model behavior and identifying potential issues like overfitting. Our methodology provides a systematic approach to building and training a classification model for brain tumor classification, leveraging transfer learning and deep learning techniques to achieve accurate and reliable results.

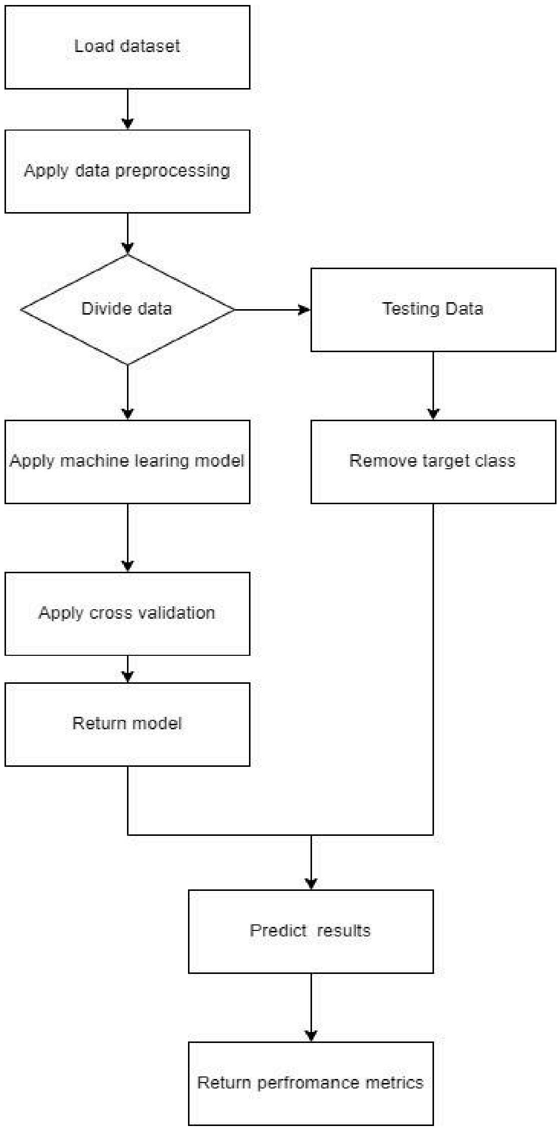


Figure 1 : Flowchart of basic machine learning model

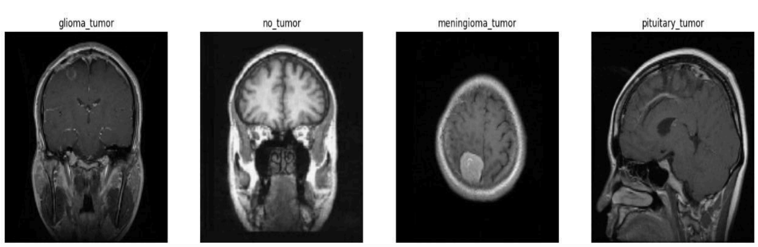


Figure 2 : Brain tumor dataset sample

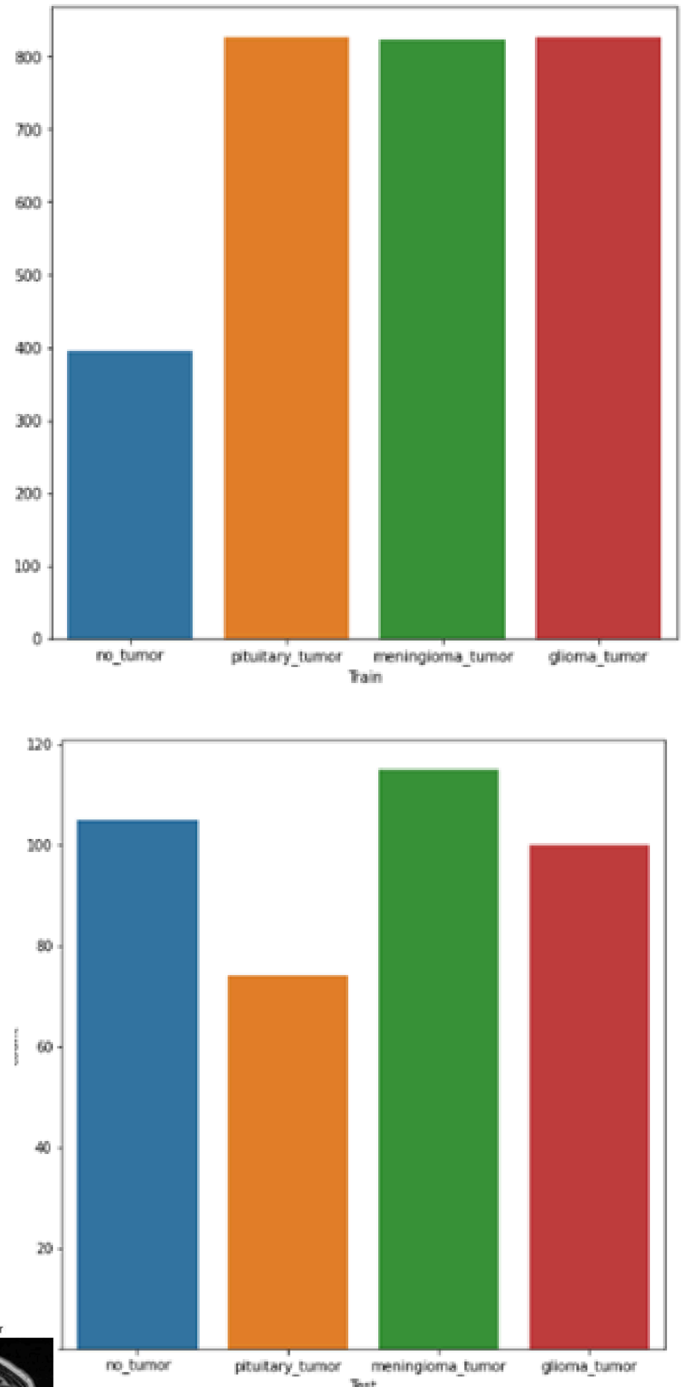


Figure 3 : Splitting the data into training and testing dataset

(b) Automated classification of skin lesions using images is a challenging task owing to the fine-grained

variability in the appearance of skin lesions. The methodology encompasses several key steps aimed at effectively analyzing skin cancer image data and developing a robust classification model. Firstly, the process begins with acquiring high-quality skin cancer image data from reliable sources like Kaggle. The pictures have all been resized to low resolution (224x224x3) RGB. It has 2 different classes of skin cancer which are listed below :
1. Benign 2. Malignant
Essential preprocessing steps involve importing necessary libraries such as NumPy, Matplotlib, Pandas, and TensorFlow/Keras for data manipulation and analysis. The dataset, typically stored in a CSV file, is loaded using Pandas, allowing access to pixel data and corresponding labels. Subsequent data exploration includes visualizing data distribution to identify any class imbalances, which are crucial for subsequent analyses. Addressing observed class imbalances, data augmentation techniques are applied. Leveraging the ImageDataGenerator from Keras, new images are generated through transformations like rotation, shifting, and flipping. Additionally, data duplication is implemented for minority classes to balance the dataset, with random optimal values selected to centralize the augmented data.

Training of neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available dataset of dermatoscopic images.This problem is tackled by using the HAM10000 ("Human Against Machine with 10000 training images") dataset. This dataset has collected dermatoscopic images from different populations, acquired and stored by different modalities. The final dataset consists of 10015 dermatoscopic images which can serve as a training set for academic machine learning purposes. Cases include a representative collection of all important diagnostic categories in the realm of pigmented lesions: Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratosis, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage,vasc). More than 50% of lesions are confirmed through histopathology (histo), the ground truth for the rest of the cases is either follow-up examination (follow_up), expert consensus (consensus), or confirmation by in-vivo confocal microscopy (confocal). The dataset includes lesions with multiple images, which can be tracked by the lesion_id-column within the HAM10000_metadata file.

Table 2 : Skin Cancer Dataset Metadata

image_ id	dx	dx_ type	age	sex	Localization
ISIC_0027419	bkl	histo	80.0	male	scalp
ISIC_0025030	bkl	histo	80.0	male	scalp
ISIC_0026769	bkl	histo	80.0	male	scalp
ISIC_0025661	bkl	histo	80.0	male	scalp
ISIC_0031633	bkl	histo	75.0	male	ear

After getting a dataset that has been resized, the data is then cleaned by removing data that is not good to use. Then the dataset is divided into training data, validation data and test data with 80:10:10 division.

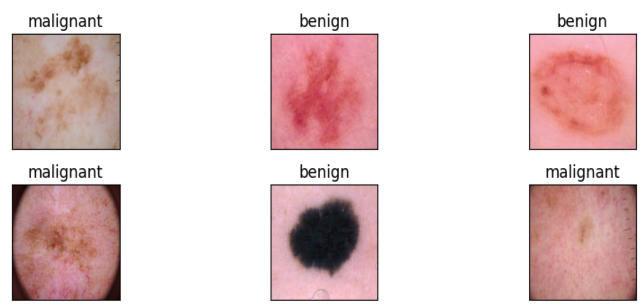
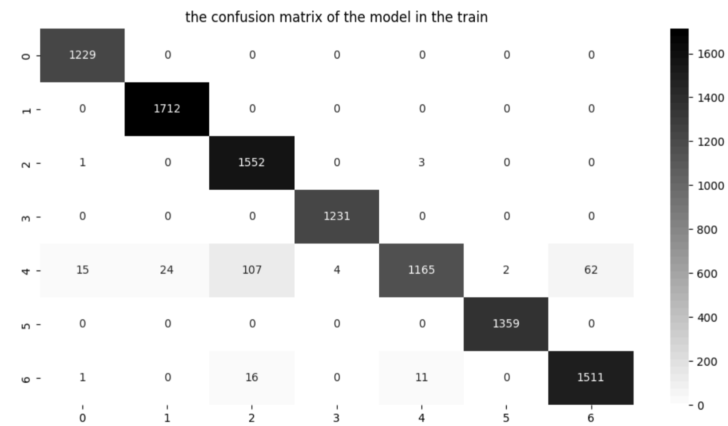


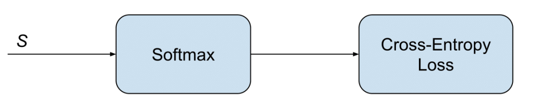
Figure 4: Skin Cancer – Melanoma Dataset

Deep Residual Network (ResNet) is an Artificial Neural Network that is created with the aim of overcoming the problem of lower accuracy when creating a plain ANN with a deeper layer than a shallower ANN. In other words, the purpose of the Deep Residual Network is to make ANN with deeper layers with high accuracy. The concept of the Deep Residual Network is to make ANN that can update the weight to a shallower layer (reduce degradation gradient). The concept is implemented using a "shortcut connection".

Figure 5 : Confusion Matrix of Skin Cancer Dataset



We applied transfer learning for skin lesion classification by slightly modifying architecture and fine-tuning weights of the ResNet50 models pre-trained on the ImageNet dataset. The modification included the use of global average pooling instead of average pooling. Hyper-parameters are important when they directly influence the attitudes of the system, since fine-tuned hyperparameters have a significant effect on the model's output. To train 10 epochs , we have used Adam optimizer, and for the batch size of 32, we set a learning rate of 0.0001.Furthermore, The categorical cross entropy loss function given below calculates the loss of class probability predicted by the soft max function. And finally measure the probability of each category.



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

I. 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.

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%

(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 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 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.

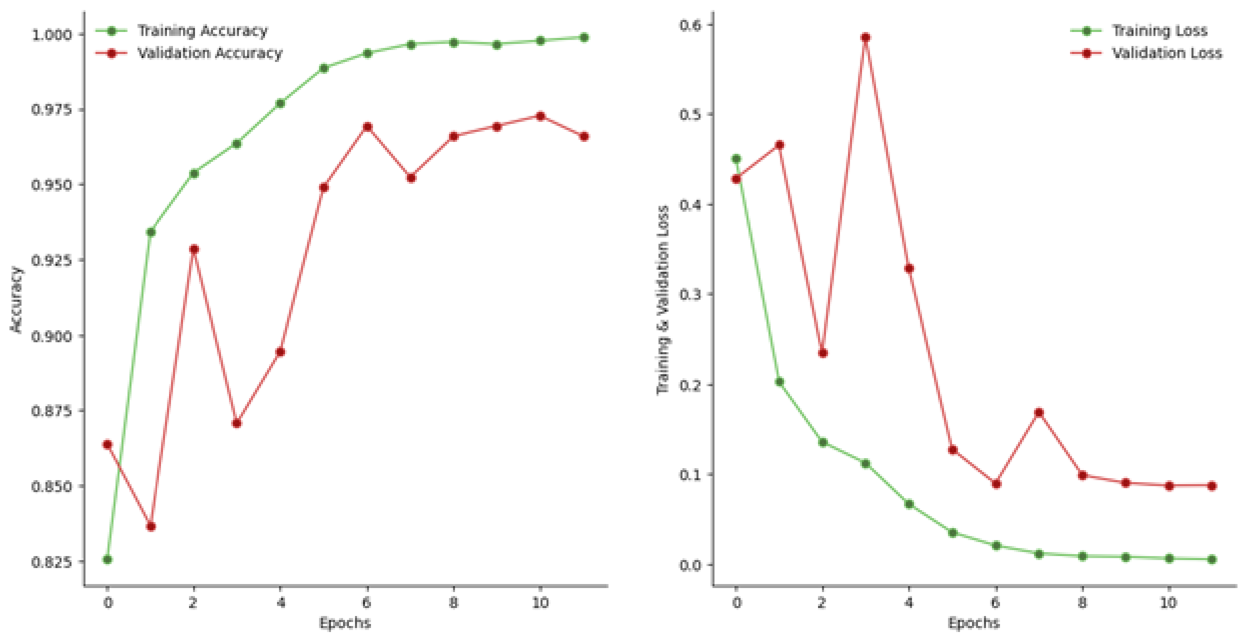


Figure 6 : Epochs vs Training and Validation Accuracy/Loss

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.

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b. Plagiarism Report :

91%

Unique Content

9%

Plagiarized content

c. Project Review Sheet :

Inhouse/ Industry _Innovation/Research:

Sustainable Goal:

Project Evaluation Sheet 2023 - 24

Class: D17 ~~A~~/B/~~C~~

Group No.: 39

Title of Project: AarogyaMitra : The Disease Diagnosis System

Group Members: Tarang Rajpal (58), Sakshi Rane (59), Reshop Nehru (48)

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life-long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
3	3	3	3	3	2	2	2	2	2	~~3~~ 2	2	2	2	3	35

Comments: ⊛ Conceptual diagram.
⊛ Paper Table for Performance Metrics
⊛ UI needs to checked./revised.
⊛ MRI Report → .pdf ; chunked ; Analysed as whole.
⊛ if not consider only one view.
⊛ Doctor → Google API) locating
⊛ Community Form. (active) needs

Lifna. CS 9/3/24.

Name & Signature Reviewer1

Engineering Concepts & Knowledge (5)	Interpretation of Problem & Analysis (5)	Design / Prototype (5)	Interpretation of Data & Dataset (3)	Modern Tool Usage (5)	Societal Benefit, Safety Consideration (2)	Environment Friendly (2)	Ethics (2)	Team work (2)	Presentation Skills (2)	Applied Engg&Mgmt principles (3)	Life-long learning (3)	Professional Skills (3)	Innovative Approach (3)	Research Paper (5)	Total Marks (50)
3	3	3	3	4	2	2	2	2	2	2	2	2	3	3	38

Comments: - Diagrams are required.
- Needs lot of improvement
- Paper needs revision/improvement elaborate it.

Date: 9th March, 2024

Sunita Sunita Suralkar

Name & Signature Reviewer 2