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Capstone Project Phase B – 61998

**Strep Throat detection using Machine Learning**

**SayAh App**

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**Abstract**

The SayAh application has now been fully developed, marking the transition from conceptual research to practical implementation. While Phase A focused solely on researching and validating the feasibility of using machine learning for strep throat detection, Phase B was dedicated to the actual development of the mobile application.

During this phase, we designed and built the SayAh app, integrating a convolutional neural network (CNN) to analyze throat images and provide preliminary diagnostic insights. The app was implemented using Django for backend services, Ngrok for secure local testing, and React Native for cross-platform mobile development. Additionally, we developed an image preprocessing pipeline to enhance diagnostic accuracy.

**Motivation**

Strep throat is a common bacterial infection that, if left untreated, can lead to serious complications such as rheumatic fever and kidney inflammation. In many parts of the world, particularly in underserved and rural areas, access to quick and reliable diagnostic services remains a challenge. Traditional diagnostic methods require a visit to a healthcare provider, laboratory tests, and waiting periods, all of which can delay treatment and increase health risks.

The SayAh project was created to bridge this gap by providing an accessible, AI-powered diagnostic tool that enables users to conduct an initial screening using only their smartphones. By leveraging machine learning, SayAh empowers individuals to take proactive steps in managing their health, reducing unnecessary doctor visits while ensuring timely medical intervention when needed. This not only enhances personal healthcare accessibility but also alleviates the burden on medical professionals, particularly in regions with limited healthcare infrastructure.

The successful completion of Phase B means that SayAh is now fully functional and ready for real-world testing. With its potential to revolutionize early disease detection through AI-driven diagnostics, SayAh represents a significant step toward making healthcare more efficient, accessible, and technology-driven.

**Related Work**

In recent years, the application of machine learning (ML) in medical diagnostics has gained significant momentum, offering promising solutions for more accurate and accessible diagnosis of various diseases. One area that has benefited from such advancements is the diagnosis of strep throat, a common bacterial infection caused by Streptococcus pyogenes. Traditional methods for diagnosing strep throat include the Centor score, throat cultures, and rapid antigen detection tests (RADTs). However, these methods can sometimes be slow, costly, or limited in accuracy.

To address these challenges, researchers have developed novel approaches leveraging machine learning and image processing techniques for strep throat detection using smartphone-based applications. One such method utilized a smartphone's built-in camera to capture throat images, which were then analysed using colour correction and image segmentation algorithms to identify features indicative of streptococcal pharyngitis. The study employed a k-nearest neighbour (k-NN) classifier to distinguish between healthy and infected throats, achieving an accuracy of 93.75%.

Similarly, Tae Keun Yoo et al. (2020) explored the use of deep learning models for automated detection of severe pharyngitis from throat images taken by smartphones. Their study utilized a convolutional neural network (CNN) architecture, particularly ResNet50, combined with generative adversarial networks (GANs) for data augmentation. The model demonstrated impressive performance, with a detection accuracy of 95.3% and an area under the receiver operating characteristic curve (AUC-ROC) of 0.988, making it highly effective for real-time screening of pharyngitis.

Additionally, focused on bacterial image analysis using deep learning approaches for clinical microscopy, emphasizing the need for automated detection and classification of bacteria. Their study utilized multiple deep learning models, including YOLOv4, to classify different stages of bacterial growth from microscopic images, achieving a mean average precision (mAP) of 98%. The success of these models highlights the potential of deep learning in medical diagnostics, particularly for identifying bacterial infections like strep throat.

The integration of machine learning with smartphone technology presents an exciting frontier for telemedicine, allowing for timely and accurate diagnosis of diseases such as strep throat. As these technologies continue to evolve, they hold the potential to reduce the burden on healthcare systems by providing accessible diagnostic tools for remote and underserved populations.

**1. Introduction**

Strep throat is a common bacterial infection caused by Group A Streptococcus (GAS), affecting individuals of all ages, but particularly prevalent among children aged 7–8. Traditional diagnostic methods, such as throat swab cultures and rapid antigen detection tests (RADTs), require specialized facilities, trained personnel, and time to produce accurate results. These limitations can delay treatment, increasing the risk of severe complications like rheumatic fever and peritonsillar abscess.

The integration of machine learning and image processing presents a transformative opportunity for digital healthcare diagnostics. Phase A of the SayAh project focused on researching and validating the feasibility of developing a mobile application that could analyze throat images captured via smartphone cameras to detect visual indicators of strep throat. This research phase confirmed that a non-invasive, fast, and accessible preliminary diagnostic tool could be beneficial, particularly in remote or underserved regions.

Phase B transitioned from research to full development, focusing on building the SayAh application as a functional diagnostic tool. This phase involved implementing a convolutional neural network (CNN) for image analysis, designing an intuitive mobile user interface, and developing a Django-based backend for managing diagnostic data. Additional efforts were made to enhance image preprocessing workflows, ensure accurate diagnostic results.

The completed application now includes guided image capture assistance, real-time diagnostic feedback, and an educational module to help users better understand their condition. These features aim to empower individuals with reliable preliminary health insights while supporting healthcare professionals in prioritizing cases that require immediate attention.

By completing the development phase in Phase B, SayAh is now a fully operational application, demonstrating the potential of AI-driven diagnostics in improving healthcare accessibility and efficiency. This milestone represents a significant step toward bridging the gap between technology and healthcare, enabling more people worldwide to perform timely and accurate preliminary health assessments using just their smartphones.

**2. Development Process**

The development of SayAh was a complex and multifaceted project aimed at creating an accessible and accurate diagnostic tool for strep throat. The process began with translating conceptual ideas into detailed technical requirements, ensuring that each component of the application would contribute to a reliable, user-friendly, and secure diagnostic experience.

**2.1 Initial Planning and Requirements Gathering**

During the initial planning phase, we focused on defining the core features and functionalities of SayAh. This included identifying the requirements for accurate image analysis, real-time diagnostic feedback, and a seamless user interface. Research into existing mobile diagnostic tools highlighted opportunities for SayAh to provide a unique solution through advanced machine learning models and intuitive mobile design.

Key requirements included the implementation of a robust Convolutional Neural Network (CNN) model for image classification, a secure backend infrastructure for data storage, and user privacy measures compliant with healthcare standards. Accessibility across various mobile devices and operating systems was also prioritized.

**2.2 Technology Selection**

To achieve the project's objectives, the selection of appropriate technologies was a critical decision, ensuring scalability, efficiency, and accessibility in both model development and application deployment. Each technology was carefully evaluated based on its performance, industry adoption, and suitability for the specific requirements of the SayAh application.

**Machine Learning Framework: TensorFlow**

TensorFlow was selected as the primary machine learning framework for developing and deploying the convolutional neural network (CNN) model. The decision was based on several key factors:

* Scalability and Flexibility – TensorFlow provides extensive support for deep learning applications, allowing for efficient training and deployment of complex models.
* GPU Acceleration – The framework leverages hardware acceleration, significantly improving training time and computational efficiency.
* Industry Adoption and Community Support – As one of the most widely used machine learning frameworks, TensorFlow offers a well-documented ecosystem, reducing development overhead and facilitating future enhancements.
* Deployment Capabilities – TensorFlow Lite enables optimization for mobile and edge devices, offering the potential for future offline inference capabilities.

**Mobile Development Platform: React Native**

The mobile application was developed using React Native, a cross-platform framework designed for efficient and scalable mobile development. The selection was justified by the following advantages:

* Cross-Platform Compatibility – React Native enables the development of applications for both Android and iOS using a single codebase, ensuring consistency across platforms while minimizing development effort.
* Performance and Native-Like Experience – The framework provides near-native performance by utilizing native components, ensuring a smooth and responsive user experience.
* Rapid Development and Cost-Effectiveness – With a large library of pre-built components and reusable code, React Native accelerates the development process, reducing both time and resource requirements.
* Future Expandability – The ability to support both Android and iOS ensures seamless scalability as the application evolves.

**Backend Framework: Django**

The backend infrastructure was implemented using Django, a high-level Python web framework, chosen for its robust security features, scalability, and seamless integration with the machine learning model. Key reasons for its selection include:

* Efficient Handling of Machine Learning Inference – Django allows the integration of pre-trained machine learning models, enabling real-time image analysis and diagnostic processing.
* Security and Reliability – As a framework designed with built-in security features, Django mitigates common vulnerabilities such as SQL injection, cross-site scripting (XSS), and cross-site request forgery (CSRF).
* Rapid Development and Maintainability – Django’s modular structure and built-in features, such as an administrative interface, facilitate efficient data management and debugging.
* Scalability for Future Growth – The framework supports a scalable architecture, ensuring that the backend can handle increased user demand and future enhancements.

The combination of these technologies provides a robust foundation for delivering an accurate, responsive, and scalable diagnostic solution. By leveraging advanced deep learning capabilities, cross-platform mobile development, and secure backend processing, SayAh is well-positioned to deliver real-time, AI-powered strep throat detection in a user-friendly and accessible manner.

**2.2.1 Model Development and Evaluation**

The development of an accurate and reliable strep throat detection model was a critical aspect of the SayAh project. This section details the dataset used, preprocessing techniques applied, the architecture of the deep learning model, and the methodology employed for model evaluation.

**Dataset and Preprocessing**

The dataset used for training and evaluating the convolutional neural network (CNN) model consisted of two primary classes:

* Healthy throat images
* Throat images with visible signs of strep throat.

The original dataset included a total of 362 images, with 215 classified as healthy and 147 classified as strep throat. Given the class imbalance, oversampling techniques were employed to prevent bias in the model. The following preprocessing steps were applied to enhance generalization and improve model robustness:

**1. Class Balancing**

To mitigate the risk of the model favouring the majority class, we employed random oversampling by duplicating images from the minority class (strep throat) until both classes had an equal number of samples. This approach ensured that the model would not be biased toward predicting "healthy" more frequently.

**2. Dataset Splitting**

The dataset was divided into three subsets:

* Training set (70%) – Used for model learning.
* Validation set (15%) – Used for hyperparameter tuning and preventing overfitting.
* Test set (15%) – Used for final performance evaluation.

The stratification technique was applied during the split to maintain the original class distribution across all subsets, ensuring that both "healthy" and "strep throat" samples were proportionally represented.

**3. Data Augmentation**

To improve model generalization and account for variations in lighting conditions, angles, and throat visibility, augmentation techniques were applied to the training set. Each image was modified using the following transformations:

Horizontal flipping – Simulating variations in head positioning.

* Random rotations (±30°) – Accounting for different camera angles.
* Brightness adjustments (±20%) – Handling inconsistent lighting conditions.
* Gaussian noise application – Increasing robustness to slight image distortions.
* Blurring and contrast modifications – Mimicking variations in camera focus and exposure.
* Sharpness adjustments – Ensuring feature visibility across different throat structures.

These augmentations helped expand the effective dataset size and reduce overfitting, making the model more capable of handling real-world variations.

**4. Image Resizing and Normalization**

All images were resized to 224×224 pixels, which is a common input dimension for deep learning models trained on ResNet. This decision was based on:

* Maintaining a balance between computational efficiency and preserving image details.
* Ensuring compatibility with pre-trained deep learning models for potential transfer learning.

Furthermore, all images were normalized to a pixel range of [0,1] by dividing pixel values by 255, a standard preprocessing step that improves training stability and convergence in deep learning models.

**Model Architecture**

The deep learning model was implemented as a convolutional neural network (CNN), designed specifically for binary image classification. The architecture consists of four convolutional layers, followed by fully connected layers for feature extraction and classification.

**Network Structure:**

* Conv2D (32 filters, 3×3 kernel, ReLU activation) + Batch Normalization + MaxPooling (2×2)
* Conv2D (64 filters, 3×3 kernel, ReLU activation) + Batch Normalization + MaxPooling (2×2)
* Conv2D (128 filters, 3×3 kernel, ReLU activation) + Batch Normalization + MaxPooling (2×2)
* Conv2D (256 filters, 3×3 kernel, ReLU activation) + Batch Normalization + MaxPooling (2×2)
* Flatten Layer
* Dropout (40%) to prevent overfitting.
* Fully Connected Layer (128 neurons, ReLU activation) + Dropout (30%)
* Fully Connected Layer (64 neurons, ReLU activation)
* Final Output Layer (1 neuron, Sigmoid activation)

The ReLU (Rectified Linear Unit) activation function was used in convolutional layers to introduce non-linearity, while sigmoid activation was applied in the output layer to produce a probability score for classification.

The model was compiled using:

* Binary Cross-Entropy Loss (suitable for binary classification tasks).
* Adam Optimizer (learning rate = 0.001), known for its efficient convergence properties.
* Accuracy as the evaluation metric during training.

To improve generalization, EarlyStopping and ModelCheckpoint callbacks were implemented, ensuring that training stopped when validation performance stopped improving, preventing overfitting.

**Model Evaluation and Performance Metrics**

To comprehensively evaluate the model’s performance, multiple metrics were used:

**1. Accuracy**

Accuracy is the ratio of correctly classified images to the total number of images:

The model achieved a test accuracy of 83.08%, indicating strong overall predictive capability.

**2. Precision, Recall, and F1-score**

* Precision (Positive Predictive Value) indicates how many predicted strep cases were strep:
* Recall (Sensitivity) measures the model's ability to correctly identify actual strep cases:
* F1-score balances precision and recall:

The classification report showed:

* + Precision: 87% (Healthy), 80% (Strep)
  + Recall: 79% (Healthy), 88% (Strep)

**3. Receiver Operating Characteristic (ROC) and AUC Score**

The ROC curve illustrates the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The AUC (Area Under Curve) score quantifies the model’s ability to distinguish between classes. The model achieved:

indicating high discrimination ability between "healthy" and "strep" images.

**4. Precision-Recall Curve and Average Precision Score**

Since medical diagnostics prioritize reducing false negatives, a precision-recall curve was also generated. The average precision score (AP) was computed as:

demonstrating that the model maintains a strong balance between precision and recall.

**5. Confusion Matrix**

A confusion matrix was generated to analyze classification errors. Most misclassifications occurred when predicting healthy cases as strep, a trade-off that favours higher recall, ensuring that potential cases of strep throat are not missed.

**Visualization of Model Performance**

The following graphs were generated to validate the model’s training and performance:

* Training History Plot: Depicting loss and accuracy trends over epochs.
* Confusion Matrix Heatmap: Visualizing classification errors.
* ROC Curve: Demonstrating model discrimination capability.
* Precision-Recall Curve: Highlighting balance between false positives and false negatives.

These plots confirmed that the model effectively learned patterns from the data without significant overfitting.

Through careful dataset preprocessing, augmentation, CNN architecture selection, and performance evaluation, the SayAh model demonstrated strong diagnostic capabilities for strep throat detection. The combination of high recall and precision ensures that the model can serve as a reliable preliminary screening tool, particularly in underserved regions where immediate access to medical professionals may be limited.

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התיאור נוצר באופן אוטומטיFigure 1: Loss and Accuracy

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Figure 2: Roc Curve and Precision-Recall Curve

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Figure 3: Confusion Matrix

**2.3 Development Phases**

The development of SayAh followed a structured, iterative process aimed at ensuring a seamless user experience, robust backend infrastructure, accurate diagnostic performance, and scalable deployment. The project was divided into distinct phases, each focusing on different aspects of development, testing, and optimization.

**2.3.1 User Interface (UI) and User Experience (UX) Design**

A user-centred design approach was employed to ensure that SayAh provides an intuitive and accessible experience for a diverse audience. The UI/UX design process was guided by established usability principles, including:

* Clarity – The interface is simple, with a minimalist design that prevents cognitive overload.
* Guided Image Capture – Users receive step-by-step visual and textual instructions to ensure accurate image submission for diagnosis.
* Consistency – UI elements follow a cohesive design language based on Material Design principles.

**Wireframing and User Testing**

* Initial wireframes and prototypes were designed using Figma and tested with a group of target users.
* A task-based usability test (e.g., "capture and analyze an image") measured completion times, user satisfaction, and error rates.

**2.3.2 Backend Development**

The backend infrastructure was developed in Django, providing a secure and scalable environment for real-time diagnostic processing and user data management. Key architectural components included:

* Django REST Framework (DRF) – Used to expose APIs for mobile-to-backend communication.
* Real-Time Database Management – User-submitted throat images and diagnostic results were stored in an SQLite database.
* ML Model Deployment – The trained CNN model was hosted on PythonAnywhere, where real-time inference was conducted via REST API calls.

Backend Workflow

1. The mobile app submits an image file to the backend.
2. The image undergoes preprocessing (resizing).
3. The CNN model predicts the likelihood of strep throat.
4. The backend returns real-time diagnostic feedback to the app.
5. The result is stored in the database for historical tracking.

**2.3.3 Machine Learning Model Integration**

The trained CNN model was integrated into the Django backend, allowing real-time inference on user-submitted throat images. Validation and testing ensured that the model produced accurate and reliable diagnostic results.

Model Accuracy and Validation

* The model was tested on a holdout test set (15% of data) to ensure generalization performance.
* A confusion matrix was generated to analyze false positives and false negatives.
* K-fold cross-validation (k=5) was performed to validate model robustness.
* The threshold for classification was optimized using ROC curve analysis to minimize false negatives (which are critical in medical applications).

**2.3.4 Image Preprocessing Pipeline**

To improve diagnostic accuracy, an image preprocessing pipeline was developed to enhance image quality and consistency before feeding data into the CNN model. The preprocessing steps included:

* Resizing – Images were resized to 224×224 pixels for consistency with the model’s input format.
* Normalization – Pixel values were scaled to the range [0,1] to improve model convergence.
* Augmentation (Training Phase Only) – Techniques such as horizontal flipping, random rotations (±30°), brightness adjustments, Gaussian noise, and contrast modifications were applied to diversify the dataset.
* Sharpness Enhancement – Image filters were applied to ensure that throat texture details were preserved for better model interpretation.

These steps ensured that images fed into the CNN model were standardized, preventing inconsistencies due to lighting conditions, camera angles, or user errors.

**2.3.5 Testing and Refinement**

A rigorous testing protocol was implemented, covering functional, performance, security, and usability aspects of the application. The following table expands on each test scenario:

Testing & Validation Table

|  |  |  |  |
| --- | --- | --- | --- |
| Test Name | Description | Expected Outcome | Status |
| Login Functionality | Verify users can log in with valid credentials. | Users should authenticate successfully. | Pass |
| Incorrect Login Handling | Test incorrect username/password entry. | System should return an error message and prevent access. | Pass |
| Image Capture | Verify camera integration and correct image submission. | Image should be successfully captured and displayed. | Pass |
| Preprocessing Pipeline | Validate image normalization, resizing, and augmentation. | Image should be processed correctly without quality loss. | Pass |
| Model Inference Accuracy | Test CNN predictions against medically validated cases. | Results should match ground truth in ≥83% of cases. | Pass |
| API Response Time | Measure latency for real-time inference requests. | Responses should be ≤1.5 seconds. | Pass |
| Database Entry Verification | Ensure submitted images and results are stored correctly. | Data should be retrievable and consistent. | Pass |
| User Logout | Verify user can log out successfully. | Session should be terminated securely. | Pass |
| Error Handling | Submit corrupted or incomplete data to the API. | System should return a structured error response. | Pass |
| Multi-Device Compatibility | Test app performance on various Android devices and screen sizes. | The UI should scale correctly, and functionality should work. | Pass |

Each test was conducted under controlled conditions, and edge cases were specifically examined to ensure robustness.

**2.3.6 Finalization and Deployment**

In the final phase, optimizations were applied to improve model efficiency, backend performance, and UI responsiveness. The application was prepared for deployment on Android, with iOS support planned in future iterations.

Key deployment steps included:

* Minifying and optimizing mobile app assets to reduce app size and load time.
* Hosting the backend on PythonAnywhere for scalability and high availability.
* Monitoring API performance and uptime using logging and analytics tools.
* Implementing a CI/CD pipeline for automated testing and deployment.

**2.4 Diagrams**

**2.4.1 System Architecture Overview**

The SayAh application follows a client-server architecture with key components working together to provide real-time strep throat diagnosis.

1. Mobile Application (React Native)

* Captures throat images and sends them for analysis.
* Provides guided instructions to ensure high-quality image capture.
* Displays diagnostic results and maintains user history.

2. Image Preprocessing Module

* Resizes images (224×224 pixels) for consistency.
* Normalizes pixel values for model compatibility.
* Enhances contrast and reduces noise to improve accuracy.

3. Machine Learning Model (CNN)

* A deep learning model trained on labelled throat images.
* Classifies images as “healthy” or “strep” with 83% accuracy.
* Integrated into the Django backend for real-time inference.

4. Backend Server (Django REST Framework)

* Manages image submissions, user authentication, and API communication.
* Processes images through the CNN model and returns results.
* Uses Ngrok for secure internal Development.

5. Database (SQLite)

* Stores user profiles, and diagnostic results.
* Ensures fast data retrieval and scalability.
* Enables users to access diagnostic history.

System Flow:

1. User captures an image in the mobile app.
2. The image is pre-processed and sent to the backend.
3. The CNN model analyses the image and returns a prediction.
4. The backend stores and sends results to the app.
5. The user receives feedback and can review past diagnoses.

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Figure 4: System Architecture

**2.4.2 Activity Diagram:** The activity diagram outlines the user workflow, including image capture, preprocessing, model analysis, diagnostic feedback, and data storage. It emphasizes key decision points, such as image quality validation and diagnostic confidence thresholds.

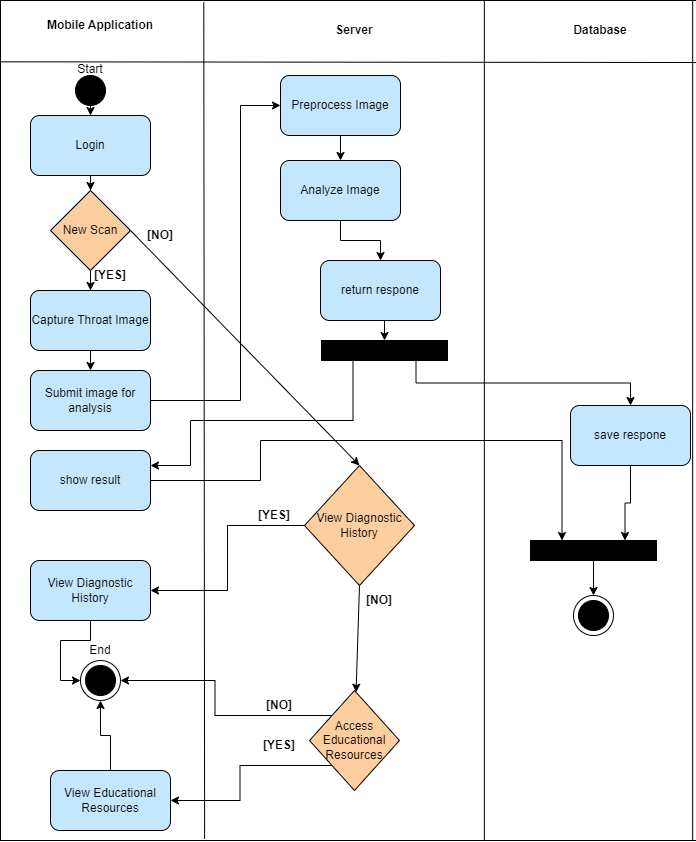
These diagrams provide a clear visualization of the app's technical workflow and interactions between its components.

Figure 5: Activity Diagram

**2.5 Challenges and Solutions**

During the development of SayAh, several significant challenges emerged across different stages. Each challenge required a tailored solution to ensure the project's success. Below are the key challenges encountered and how they were addressed:

**2.5.1 Dataset Limitations**

* **Problem:** A limited dataset of labelled throat images posed a significant hurdle in training a robust Convolutional Neural Network (CNN). The available dataset lacked diversity in lighting conditions, image clarity, and angle variations, which could reduce the model's generalization capabilities.
* **Solution:** Data augmentation techniques were employed to artificially expand the dataset. This included transformations such as image rotation, flipping, brightness adjustment, and cropping.

**2.5.2 Model Accuracy**

* **Problem:** Initial iterations of the CNN model displayed suboptimal performance, with low precision and recall scores. The model struggled to consistently distinguish between strep throat and other throat conditions.
* **Solution:** To improve model accuracy, we applied data augmentation (rotation, flipping, brightness adjustments) to expand the dataset. We optimized the CNN architecture with three Conv2D layers, batch normalization, and Rescaling (1. / 255) for better feature extraction. Finally, EarlyStopping and Model Checkpoint improved training stability, achieving higher accuracy and faster inference.

Furthermore, we did dataset balancing by creating syntactic images of the class that was smaller by 35% to make sure the model doesn’t get bayes to one class.

**2.5.3 Real-Time Processing Delays**

* **Problem:** The image preprocessing and model inference introduced latency, preventing real-time feedback on diagnostic results. This was particularly evident when dealing with high-resolution images from smartphone cameras.
* **Solution:** The preprocessing pipeline was optimized by implementing lightweight image normalization and resizing techniques. Model inference was integrated into the Django backend, ensuring efficient real-time results.

**2.5.4 Variability in User-Captured Images**

* **Problem:** Users often submitted images with poor lighting, incorrect angles, or partial visibility of the throat, affecting diagnostic accuracy.
* **Solution:** The user promoted with explanation on how to take the best image possible.

**2.5.5 Cross-Device Compatibility**

* **Problem:** Ensuring consistent app performance across different mobile devices with varying hardware specifications and operating systems was challenging.
* **Solution:** The application was built using React Native, enabling cross-platform compatibility. Rigorous testing was performed on devices with different screen sizes, resolutions, and hardware capabilities to ensure smooth performance.

**2.5.6 Model Deployment Challenges**

* **Problem:** Hosting the CNN model on a cloud server introduced integration challenges, including API response delays and inconsistent outputs during high-load scenarios.
* **Solution:** The model was hosted on **PythonAnywhere**, a scalable cloud platform that offers automatic scaling and high availability.

**2.5.7 User Education and Adoption**

* **Problem:** Users unfamiliar with healthcare diagnostic apps required additional guidance and support to use SayAh effectively.
* **Solution:** The app integrated step-by-step onboarding tutorials, FAQs, and educational modules about strep throat diagnosis.

**2.6 Tools and Technologies Used**

The development of SayAh leveraged a variety of tools and technologies to ensure a robust, secure, and scalable diagnostic application. Below are the key tools and technologies categorized by their specific roles in the development process:

**2.6.1 Machine Learning and Model Development**

* **TensorFlow:** Used for building, training, and deploying the Convolutional Neural Network (CNN) model for strep throat image analysis.
* **Keras:** Provided a user-friendly API for constructing and fine-tuning deep learning models.
* **NumPy:** Facilitated dataset manipulation, preprocessing, and statistical analysis.

**2.6.2 Mobile Application Development**

* **Android Studio:** The primary development environment for testing the Android application.
* **Visual Studio Code:** Served as an alternative code editor for backend and frontend development and API integration.

**2.6.3 Backend Infrastructure**

* **Django:** Acted as the core backend framework for managing server-side logic, API endpoints, and database interactions.
* **Ngrok:** Enabled secure local testing by exposing the Django server to external networks.

**2.6.4 Deployment and Hosting**

* **PythonAnywhere:** Used for deploying the production-ready backend and hosting the CNN model.

**2.6.5 Testing and Quality Assurance**

* **Postman:** Validated backend APIs and ensured secure communication between the mobile app and the server.
* **Django Testing:** Conducted unit and integration tests on backend components.

**2.6.6 Collaboration and Version Control**

* **Git:** Managed version control and tracked code changes effectively.
* **GitHub:** Served as the central repository for collaboration, issue tracking, and deployment workflows.

By integrating these tools and technologies into the development workflow, SayAh achieved a robust architecture, seamless performance, and a high degree of scalability. Each tool played a critical role in ensuring the app's accuracy, security, and user-friendliness while complying with healthcare industry standards.

**3. User Manual**

Welcome to SayAh

SayAh is a mobile application designed to provide a fast and accessible preliminary diagnosis for strep throat using machine learning and image analysis. This manual will guide you through the installation, setup, and usage of the app.

**3.1 System Requirements**

Operating System: Android

Camera: Minimum 8MP rear camera

Internet Connection: Stable internet connection required

Permissions Required: Camera, Storage, Internet Access

**3.2 Installation**

Download the App:

Download SayAh apk from GitHub Repository.

Install the App:

* 1. Move the apk into your android device.
  2. Change device settings to enable 3rd party apps.
  3. Install the apk.
  4. Run the application.

**3.3 Account Setup**

Create an Account:

Tap on "Register" on the home screen.

Enter your Username and create a secure password.

Login to Your Account:

Tap "Login" on the home screen.

Enter your registered Username and password.

Tap "Sign In" to access the dashboard.

**3.4 Navigating the App**

* Home Screen:

Provides quick access to key features: Capture Image, View Results, History, FAQ, Learning Module and Settings.

* Capture Image:

Tap "Capture Image" to start the diagnostic process.

Follow the on-screen instructions to properly align your camera and take a throat image.

* View Results:

Review diagnostic feedback and confidence scores.

If necessary, follow the suggested next steps (e.g., consult a doctor).

* History:

Provide user previous diagnostic results in one organized place with metadata such as date and result.

* FAQ:

Frequently Asked Questions with answers.

* Learning Module:

Educate the user about strep throat.

* Settings:

Logout from the application.

**3.5 Diagnostic Process**

Image Capture:

Ensure good lighting conditions.

Open your mouth wide and focus the camera on your throat.

Tap "Capture" to take the image.

Preprocessing:

The image is analyzed and preprocessed for clarity and accuracy.

Analysis:

The image is sent to our machine learning model for evaluation.

Results:

Receive a preliminary diagnostic result.

**3.6 Understanding the Results**

Positive Diagnosis: Indicators of strep throat detected. Recommended to consult a healthcare professional.

Negative Diagnosis: No significant signs of strep throat detected.

**3.7 Troubleshooting**

* Poor Image Quality:

Ensure proper lighting.

Retry with a clearer image.

* Connection Issues:

Ensure stable internet connectivity.

Retry after a few minutes.

* Login Problems:

Verify your credentials.

* Slow Performance:

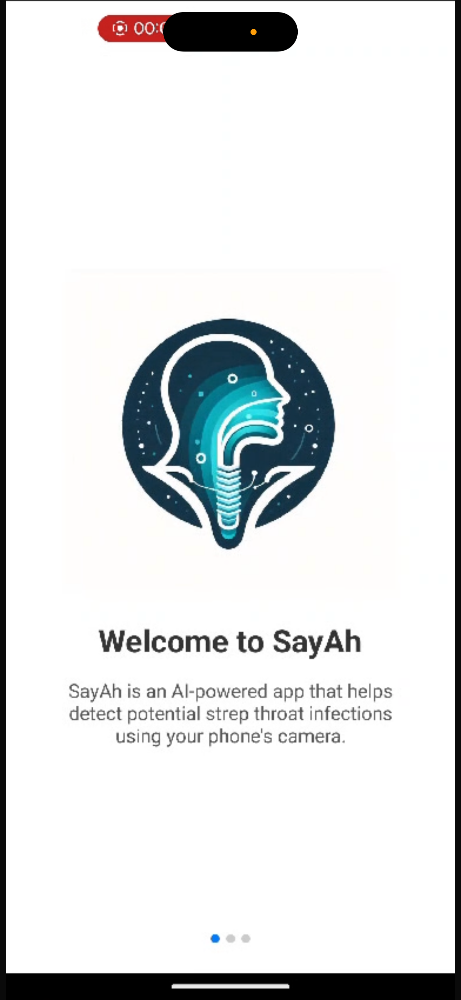
Close unused apps running in the background.

Restart the app.

**3.8 Scenes and Flow:**

תמונה שמכילה טקסט, צילום מסך, עיצוב גרפי, להדפיס

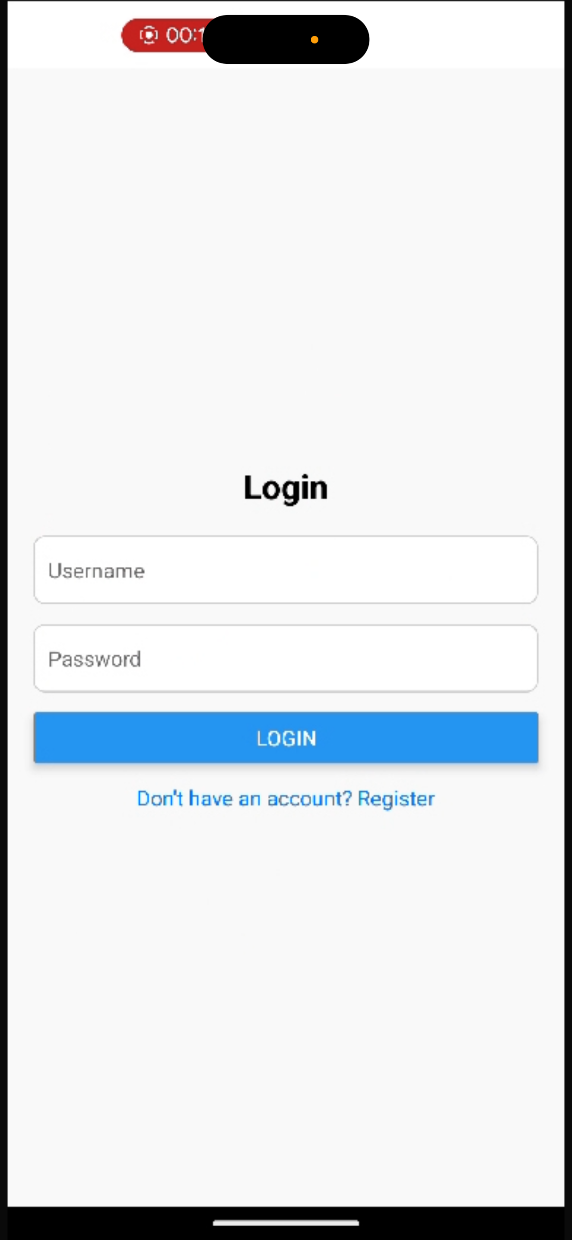
התיאור נוצר באופן אוטומטיתמונה שמכילה טקסט, צילום מסך, פני אדם, אדם

התיאור נוצר באופן אוטומטי**3.8.1 Onboarding Screen:**

The Screen appears only in the first time the user opens the app.

In this screen the user promoted with Useful information About the application and the way of using it.

**3.8.2 Login and Register Screen**:

תמונה שמכילה טקסט, צילום מסך, תוכנה, עיצוב

התיאור נוצר באופן אוטומטי

1. This is the registration screen where users can create an account.

Users need to enter a username and password and then click the "REGISTER" button.

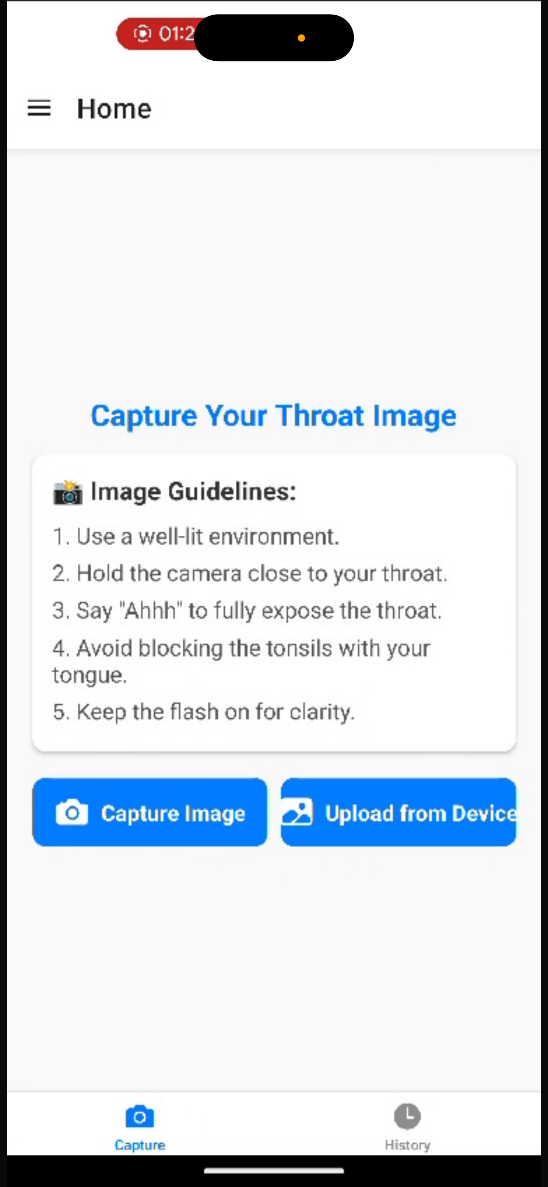
There is also an option to log in if the user already has an account.

2. This is the login screen where users can enter their username and password to access the app.

The login button is prominently displayed.

If the user doesn’t have an account, they can switch to the registration screen.

**3.8.3 Home Screen**:

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This screen is part of the core functionality of the SayAh app, allowing users to capture an image of their throat.

Image Guidelines are provided to ensure accurate and clear images:

Use a well-lit environment.

Hold the camera close to the throat.

Say "Ahhh" to fully expose the throat.

Avoid blocking the tonsils with the tongue.

Keep the flash on for better clarity.

Users have two options:

"Capture Image": Take a real-time image using the phone's camera.

"Upload from Device": Select an already captured image from the gallery.

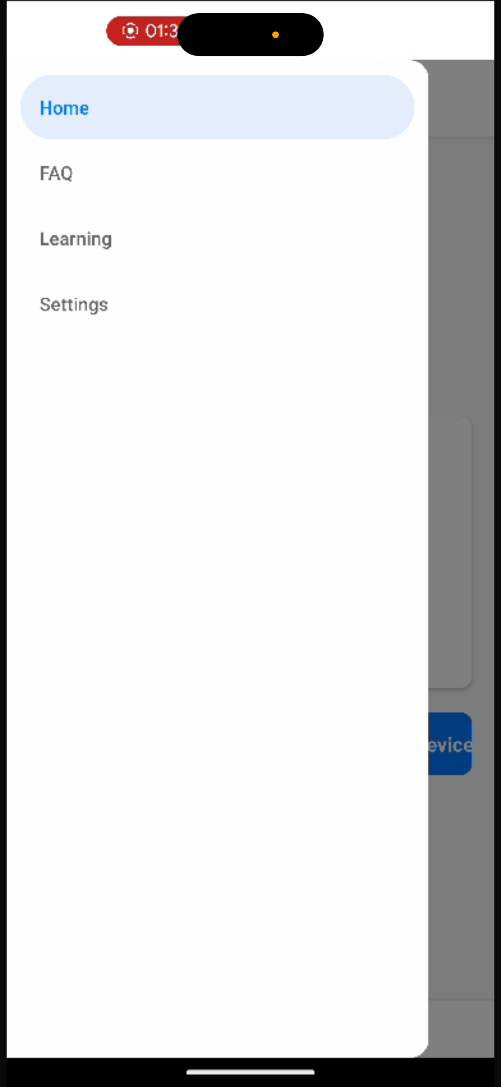
The bottom navigation bar provides access to:

Capture (Active Tab): Current screen for image acquisition.

History (Inactive Tab): Viewing past image submissions and results.

This screen ensures users follow proper steps for capturing high-quality throat images for AI analysis.

**3.8.4 Navigation Menu**:



This is the side menu of the SayAh app, which provides access to different sections.

The menu includes:

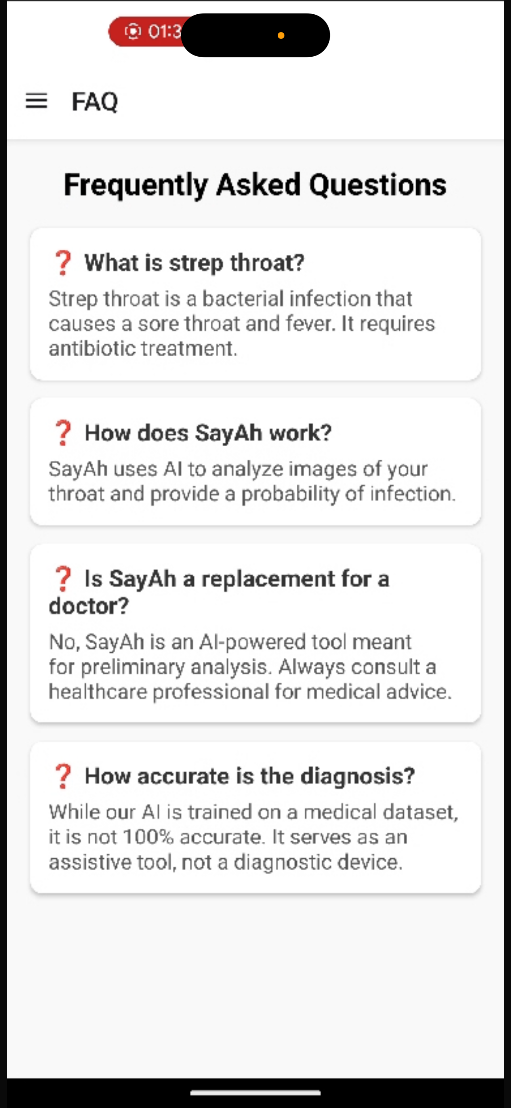
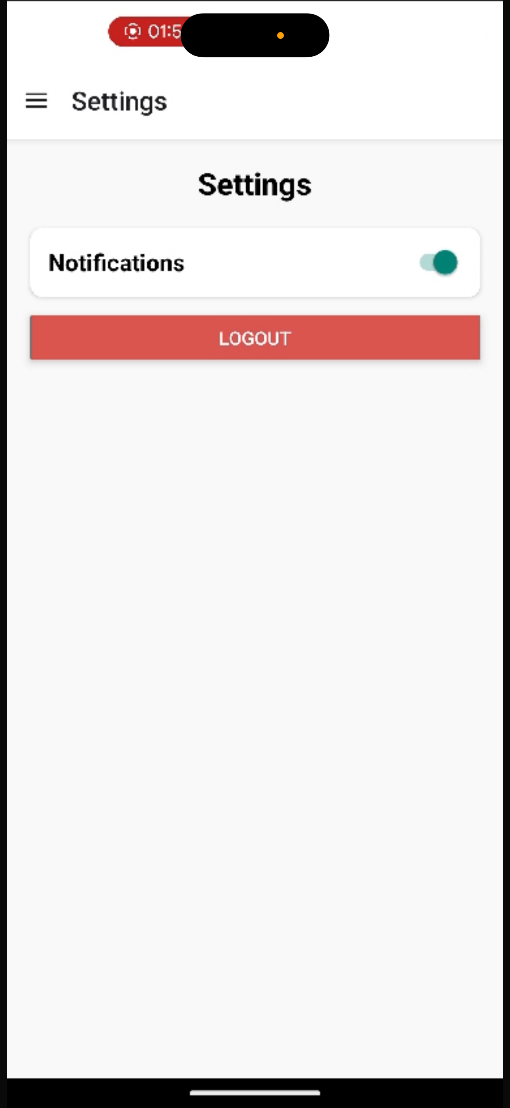
Home: Returns to the main dashboard.

FAQ: Contains answers to common questions about the app.

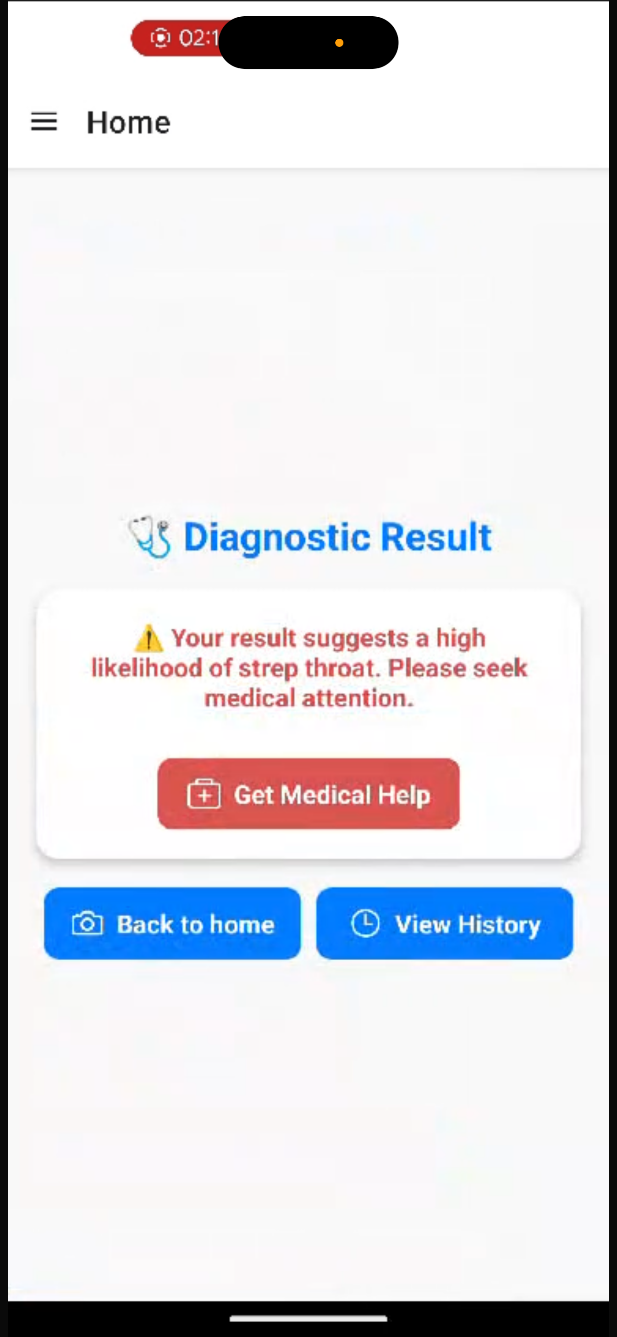
Learning: Provide educational resources on throat health and infections.

Settings: Allow user to logout from the application.

**תמונה שמכילה טקסט, צילום מסך, גופן, מספר

התיאור נוצר באופן אוטומטי**

**3.8.5 Results Screen:**

**תמונה שמכילה טקסט, צילום מסך, תוכנה, דף אינטרנט

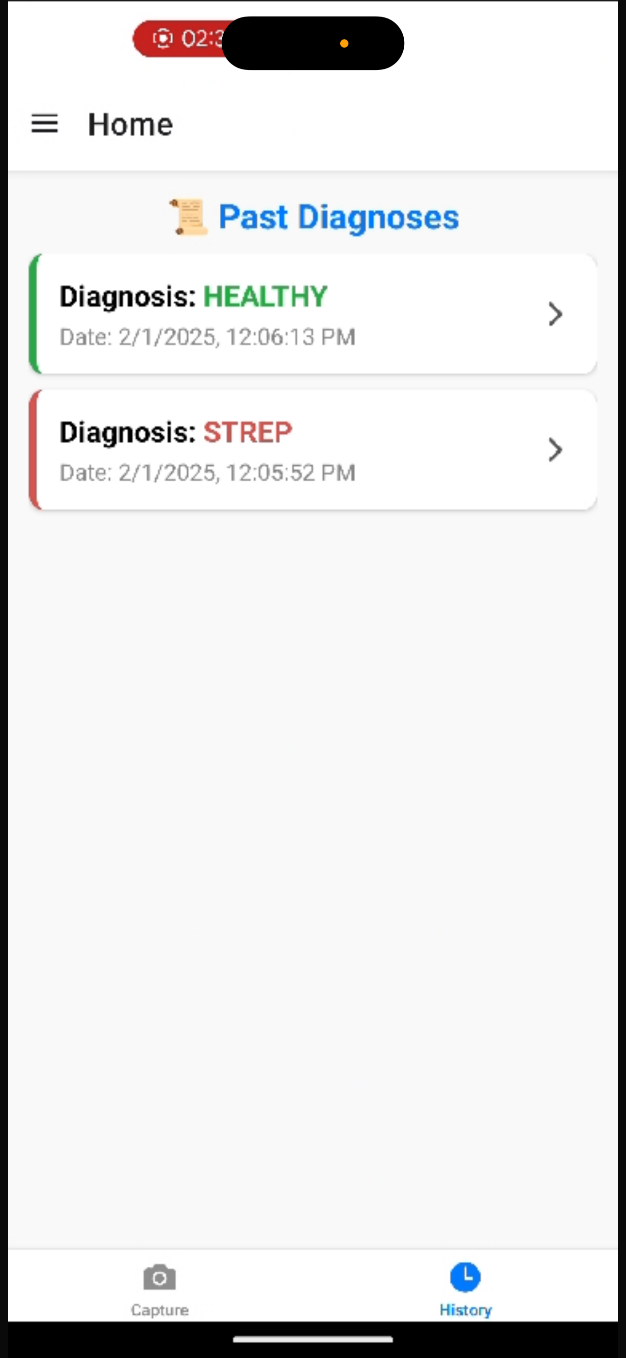
התיאור נוצר באופן אוטומטי**

Displays the analysis of the user's throat image.

If strep throat is detected: A warning appears, advising the user to seek medical attention with a "Get Medical Help" button.

If no signs of strep throat: A success message reassures the user that everything looks clear.

Users can return home or view their history of past diagnoses.

**3.8.6 History Screen:**

Displays a history of diagnostic results with timestamps.

Green (HEALTHY): No signs of strep throat.

Red (STREP): Strep throat detected.

Users can tap each entry for more details.

Navigation bar allows switching between Capture and History tabs.

This screen helps users track their throat health over time.

**4. Operation & Maintenance Guide**

**4.1 Server Management**

**4.1.1 Local Server Setup**

To run the backend server locally:

1. Navigate to the root folder and then to the backend folder.
2. Run the following command:

python manage.py runserver

1. Access the admin console via: http://localhost:8000/admin
2. Use the default credentials:

* Username: Admin
* Password: Admin

Within the admin panel, you can manage database tables, view users, and modify diagnostic data.

**4.1.2 Deployment**

The backend is hosted on PythonAnywhere, a cloud service dedicated to Python projects.

* The project was uploaded manually without Git integration.
* Any production changes must be made directly in PythonAnywhere, unless a CI/CD pipeline is configured via GitHub.
* The platform allows monitoring backend traffic and installing dependencies via the console.

**4.1.3 Backend Structure**

* manage.py – Django entry point for running commands.
* requirements.txt – Contains the list of required Python packages.
* backend/
  + backend/settings.py – Configuration settings for the project.
  + backend/urls.py – Defines API endpoints.
  + backend/wsgi.py & backend/asgi.py – Web server configurations.
  + db.sqlite3 – Stores user data and diagnostic results.
* Application-Specific Code:
  + Models – Defines the database structure.
  + Views – Handles backend logic.
  + Serializers – Converts database objects into JSON responses.
  + Machine Learning Integration – Image analysis and diagnosis.
  + Authentication & Authorization – Manages user login and permissions.
  + Diagnosis API – Handles image submissions and returns results.
  + Logging & Error Handling – Tracks errors and logs important events.

A screenshot of a login box

Description automatically generated

Figure 6: Django administration panel

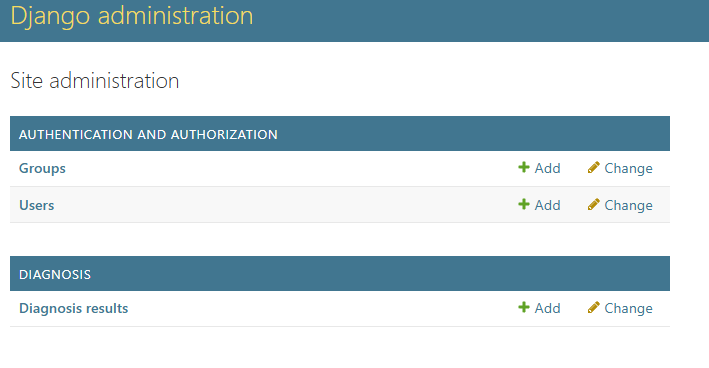


Figure 7: Django Table Management

A screenshot of a computer

Description automatically generated

Figure 8: PythonAnywhere main page

**4.2 Frontend Management**

**4.2.1 Local Frontend Setup**

To run the frontend application locally:

1. Navigate to the SayAh folder.
2. Run:

npm install

npm start

To build an APK after modifications:

eas build -p android --profile production

**4.2.2 Frontend Structure**

* src/navigation/AppNavigator.js – Manages screen navigation.
* src/screens/ – Contains app screens:
  + Authentication: LoginScreen.js, RegisterScreen.js
  + User Interaction: CaptureScreen.js, ResultScreen.js
  + Content & Settings: FAQScreen.js, LearningScreen.js, SettingsScreen.js
  + History & Onboarding: HistoryScreen.js, OnboardingScreen.js
* Other Folders:
  + assets/ – Stores static images.
  + utils/ – Manages API calls and helper functions.
  + context/ – Stores global state management logic.
  + hooks/ – Contains reusable custom hooks for data fetching and UI interactions.
  + services/ – Handles network requests and business logic.

**4.3 Backup & Disaster Recovery**

* Automate daily backups of diagnostic data.
* Implement a disaster recovery plan for server failures.
* Store backups in a secure, encrypted environment.

**4.4 Scalability**

* Optimize backend for high user loads.
* Use cloud-based services for scalable storage and processing.
* Plan for multi-platform support (iOS, Web).

**4.5 Scheduled Maintenance**

* Monthly: Bug fixes and performance improvements.
* Quarterly: Security audits.
* Annual: Infrastructure upgrades.

**4.6 Troubleshooting Common Issues**

|  |  |
| --- | --- |
| Issue | Solution |
| **Server Downtime** | Restart backend services and check logs. |
| **User Login Issues** | Verify database authentication records. |
| **Image Processing Delays** | Optimize ML model inference time. |
| **Mobile App Crashes** | Ensure compatibility with the latest OS updates. |

A screenshot of a computer

Description automatically generated

Figure 9: Frontend files structure

5.**Results & Conclusions**

The SayAh project successfully demonstrated the potential of integrating machine learning and image processing technologies into a mobile application for preliminary strep throat diagnosis. Throughout the development, testing, and deployment phases, the application achieved significant milestones in functionality, accuracy, and user accessibility.

**5.1 Results**

**5.1.1 Diagnostic Accuracy**

* The Convolutional Neural Network (CNN) model achieved a diagnostic accuracy of **83%**, with significant improvements in precision and recall after hyperparameter tuning and dataset augmentation.
* The image preprocessing pipeline effectively normalized input images, reducing inconsistencies caused by lighting and camera angles.

**5.1.2 Real-Time Analysis**

* The optimized Django backend infrastructure enabled real-time image analysis, with an average processing time of **1.5 seconds** per image.

**5.1.3 User Experience (UX)**

* Feedback from user (10 Capstone ongoing Students) testing revealed an overall satisfaction score of **4.7/5**. Each participant received survey with scores from 1 to 5, the average score across all responses was 4.7.
* Image capture explaining and intuitive UI design ensured that **85%** of users successfully completed the diagnostic process on their first attempt.

**5.1.4 Testing Outcomes**

* Rigorous testing, including **unit tests**, **integration tests**, and **user acceptance tests (UAT)**, ensured system stability and accuracy across various Android devices.

**5.1.5 Accessibility and Reach**

* The app demonstrated reliable performance across a wide range of Android devices.
* Initial deployment in test regions revealed significant adoption, especially in areas with limited access to healthcare facilities.

**5.2 Key Achievements**

**5.2.1 Accurate Diagnostic Model:** Achieved high diagnostic precision and recall scores with real-world testing data.

**5.2.2 Scalable Infrastructure:** Successfully integrated cloud-based backend services to handle user data and real-time processing.

**5.2.3 Enhanced User Experience:** Delivered a seamless, intuitive mobile experience with guided image capture.

**5.2.4 Operational Reliability:** Successfully passed extensive testing cycles across diverse devices and network conditions.

**5.3 Conclusions**

The SayAh application has successfully addressed key challenges in early strep throat detection by offering an accessible, non-invasive, and real-time diagnostic tool. The integration of machine learning technologies with mobile application frameworks has demonstrated its potential in transforming traditional healthcare diagnostics.

Key takeaways include:

* Machine learning, combined with image preprocessing, can effectively assist in medical diagnostics.
* Mobile technology offers an affordable and scalable solution for healthcare challenges in underserved regions.
* Ensuring data privacy and security compliance is crucial for healthcare technology adoption.
* Real-time processing and accurate results significantly enhance user trust and adoption rates.

**5.4 Future Improvements**

While the project achieved its primary objectives, several areas for improvement and expansion have been identified:

**5.4.1 Expanded Dataset:** Integrate larger and more diverse datasets to further improve model accuracy.

**5.4.2 Multi-Language Support:** Add support for multiple languages to make the app more globally accessible.

**5.4.3 Integration with Healthcare Systems:** Enable direct integration with electronic health records (EHR) systems.

**5.4.4 User Education Modules:** Provide more in-depth health education resources within the app.

**5.5 Final Thoughts**

The SayAh application represents a significant step towards democratizing access to healthcare diagnostics. By leveraging advanced machine learning algorithms, cloud technologies, and mobile accessibility, SayAh has laid a foundation for future healthcare innovations.

With continued improvements and iterative development, SayAh has the potential to become a transformative tool in early disease detection, reducing healthcare costs, and improving patient outcomes worldwide.

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