KidniFy – A mobile based patient care application for Kidney Patients

2023-032

Project Proposal Report

Marasinghe M.M.K.L.

B.Sc. (Hons) Degree in Information Technology specializing in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

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DECLARATION

We declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The supervisor/s should certify the proposal report with the following declaration.

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

Signature of the Supervisor:	2023.03.	
Signature of the Co-Supervisor:	2023.03.	

ABSTRACT

CKD is a significant health problem in Sri Lanka, with several factors contributing to its high prevalence. Environmental, occupational, and lifestyle factors all play a role in the development of CKD. To improve the accuracy of CKD diagnosis and predict disease progression, machine learning techniques such as supervised training, computer vision, and IoT devices are being employed through a mobile application. The proposed method involves using deep learning-based algorithms to analyze radiographs of kidney patients. Image processing techniques are used to detect and classify kidney abnormalities, including stones, tumors, and cysts, from radiographs captured using a smartphone camera. Preprocessing the images to enhance contrast and remove noise, followed by feature extraction using CNN, is necessary to ensure accurate results. The app uses multimodal image fusion techniques to allow users to upload a range of medical images for more accurate diagnosis. The standardization feature helps users track their progress over time. The mobile-based image processing technique has the potential to provide a cost-effective and accessible solution for CKD diagnosis and monitoring. It can improve the quality of life for CKD patients in Sri Lanka by providing early detection and timely interventions. The integration of machine learning techniques in healthcare is a growing trend that has significant potential to revolutionize the diagnosis and treatment of various diseases.

Keywords: Chronic kidney disease (CKD), Sri Lanka, machine learning, supervised training, computer vision, IoT devices, deep learning, radiographs, image processing, multimodal image fusion.

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LIST OF ABBREVIATION

AIE - Aggregation-Induced Emission

AI - Artificial Intelligence

APIs - Application Programming Interfaces

App - Application

App Store - Apple App Store

AWS - Amazon Web Services

CAD - Computer-Aided Diagnosis

CKD - chronic kidney disease

CNN - Convolutional Neural Network

CT - Computed Tomography

DICOM - Digital Imaging and Communications in Medicine

GFR - Glomerular Filtration Rate

HSA - Human Serum Albumin

IHS - Intensity-Hue-Saturation

ML - Machine Learning

MRI - Magnetic Resonance Imaging

NIfTI - Neuroimaging Informatics Technology Initiative

NMF - Non-negative Matrix Factorization

PCA - Principal Component Analysis

PET - Positron Emission Tomography

POC - Point-of-Care

ResNet - Residual Network

ROC - Receiver Operating Characteristic

ROI - Region-of-Interest

SVM - Support Vector Machine

UE - Ultrasound Elastography

VGG - Visual Geometry Group

1 INTRODUCTION

1.1 Background and Literature Survey

CKD is a primary health problem affecting many people in Sri Lanka and the world. The early detection of CKD is crucial to prevent illness over time to the end stage of kidney failure that mandates either undergoing dialysis or receiving a kidney transplant. Medical imaging is essential for diagnosing CKD, providing a non-invasive and accurate visualization of the kidneys [1]. Medical images for the diagnosis of CKD can be obtained using various imaging techniques, like ultrasound, CT, MRI and PET. Ultrasound is a commonly used modality for the initial evaluation of CKD due to its non-invasive nature and relatively low cost. CT and MRI are also widely used for diagnosing and staging CKD, providing detailed images of the kidneys and surrounding structures. PET is a newer modality that can provide helpful information about the kidneys and has shown promise in the diagnosis of CKD [2].

In recent years, medical imaging and image processing techniques have significantly advanced the early detection and diagnosis of CKD. These techniques can extract meaningful information from medical images and help identify subtle kidney changes that may indicate the presence of CKD. Image processing techniques, such as segmentation, feature extraction, and classification algorithms, can be used to analyze medical images and extract relevant features that aid in the diagnosis of CKD [3].

A mobile app that uses medical images and image processing techniques to identify and diagnose CKD could significantly impact patient outcomes. The app could provide a fast and convenient way for patients to obtain a preliminary diagnosis and help them monitor the progression of their disease. The app could also assist healthcare providers in making more accurate and timely diagnoses, leading to better patient outcomes.

In 2016, Pallavi Vaish, R Bharath, P Rajalakshmi and U. B. Desai developed a smartphone-based automatic abnormality detection of kidneys in ultrasound images. Traditional methods of telesonography are limited by the need for constant expert availability and data connectivity to the device. To overcome these limitations, the authors propose a computer-aided diagnosis (CAD) system for automatically detecting abnormalities in ultrasound images. However, integrating CAD algorithms into existing ultrasound scanners can be challenging due to restrictions on installing new software. The authors suggest using smartphones as external computing devices with the developed app as a solution.

The app uses the algorithm of Viola-Jones and extraction of texture features, succeeded by a support vector machine (SVM) classifier for automated diagnosis. The algorithm detected kidney stones and cysts with an accuracy of 90.91%. While the developed app shows promise for automated diagnosis, there are potential gaps in the research that should be addressed, such as the need to expand the study to include other potential kidney issues and validate the app's effectiveness on more extensive and more diverse datasets [4].

In 2021, Israa Alnazar and the team conducted a survey assessing the role of advanced imaging modalities and artificial intelligence (AI) in evaluating kidney function and structure, which is essential for the diagnosis of CKD. Different medical imaging modalities, such as Magnetic Resonance Imaging (MRI), Ultrasound Elastography (UE), Computed Tomography (CT), and scintigraphy (PET, SPECT), were summarized for their ability to non- intrusive retrieval of data that can detect alterations in renal tissue properties and performance. Integrated with machine learning techniques, texture analysis was introduced as a promising supplementary approach for predicting the decline in renal function. Moreover, the survey discussed how AI could comprehensive framework to evaluate renal function, from segmentation to disease prediction, highlighting the role of deep learning as an innovative approach to renal function diagnosis. The paper concluded that integrating AI with advanced imaging modalities could improve renal dysfunction monitoring and prediction [5].

In 2018, Shaymaa Akraa created a urinalysis device that operates via mobile phones, specifically designed for chronic kidney disease (CKD) patients. This device allows for fast and precise quantification of human serum albumin (HSA) through urinalysis, utilizing an aggregation-induced emission (AIE) nanomaterial bio probe in conjunction with smartphones. The authors address the device agnosticism issue by custom-designing a standardized imaging enclosure that ensures uniform imaging conditions, regardless of the camera position and physical dimensions of the smartphone, orchestrating an image processing procedure that yields constant the intensity values of image color irrespective of the imaging software and the sensor of the camera employed, and designing a multi-platform mobile application that can be scaled up to accommodate growth, flexible enough to adapt to changes, and robust enough to be resilient to data loss, and has a low hardware requirement. An initial assessment of the device showed the efficacy of the suggested solution and the feasibility of implementing a mobile-based device for CKD patients to conduct urine testing at the point of care (POC) on a regular basis to monitor their health status themselves, without the inconvenience of frequent doctor visits. However, the paper must provide detailed information on the nanomaterial bio probe, or the exact methods used for image processing and analysis. Additionally, further testing and validation of the device's accuracy and reliability would be necessary before widespread adoption. In summary, the paper presents an innovative approach to address the problem of device agnosticism by developing a smartphone-based urinalysis device for CKD patients. While the initial evaluation shows promising results, additional research is necessary to evaluate the effectiveness and practicality of the device entirely [6].

In 2021, Hanjie Zhang and the team published an article highlighting the significance of deep learning strategies, particularly convolutional neural networks, in analyzing radiological and tissue specimen images. The article discusses how this approach can advance the diagnostic process significantly, especially since the conventional manual method can be prone to interobserver variability and time-consuming. The authors focused on using convolutional neural networks for image classification and segmentation and its application in renal medicine. They presented concise explanations of neural networks using convolutional techniques and their structural layout of a system utilized for image analysis, along with examples of application in analyzing images in nephrology. The article aims to introduce the fundamental concepts of image analysis using convolutional neural networks and demonstrate their potential in medical diagnostics [7].

In conclusion, while medical imaging and image processing have been used together in some cases, several challenges still need to be addressed. Despite these challenges, combining medical imaging and image processing offers promising opportunities for improving healthcare outcomes and advancing medical research.

And also, the early detection and diagnosis of CKD are critical in preventing illness over time to end-stage renal failure. Medical imaging and image processing techniques have shown great promise in the early detection and diagnosis of CKD. Developing a mobile app that leverages these techniques could significantly impact patient outcomes, making it a promising area of research.

1.2 Research Gap

Although diagnostic image-modalities such as CT and MRI are widely used for the purpose of diagnosis and monitoring of CKD, the effectiveness of traditional methods for analyzing kidney medical images on mobile devices is limited. Previous research has focused on the use of algorithms such as Viola-Jones for image analysis, which lack accuracy and speed when compared to newer technologies.

To address this gap, this study proposes the use of Convolutional Neural Networks (CNNs), which have demonstrated higher accuracy and faster analysis capabilities than Viola-Jones. Additionally, we will incorporate multimodal image fusion, a technique that allows for the simultaneous analysis of multiple images to improve the accuracy of diagnosis.

Moreover, we will utilize standardization to allow for progress tracking of kidney health over time through mobile app use. This approach will enable patients to upload medical images periodically, allowing users to monitor changes in the condition of their kidneys.

While previous research has explored the use of CNNs and multimodal image fusion for analysis of medical images, there has been limited focus on the application of these methods specifically for kidney medical image analysis in mobile apps. Additionally, the use of standardization to track progress in kidney health through mobile apps is a new approach that requires further investigation.

Therefore, this study aims to develop and evaluate a mobile app-based framework for CKD diagnosis and monitoring, utilizing CNNs, multimodal image fusion, and standardization. The effectiveness and accuracy of the proposed framework will be compared to traditional methods to assess its potential benefits in improving the diagnosis and monitoring of CKD.

In conclusion, while previous research has explored the potential of newer technologies for medical image analysis, the application of these methods for kidney medical image analysis in mobile apps is an area that requires further investigation. The objective of this study is to fill this gap and contribute to the development of more accurate and efficient methods for CKD diagnosis and monitoring in mobile app-based platforms.

2 RESEARCH PROBLEM

Medical imaging is a critical aspect of the diagnosis and management of kidney diseases, as it allows for accurate visualization and measurement of the structure and function of the kidneys. However, even with traditional methods of analyzing medical images for kidney health, errors can occur due to the complexity of the renal anatomy and the variability in interpretation. These errors can lead to serious consequences for patients, including misdiagnosis, delayed treatment, and poor outcomes. The potential for missed abnormalities in medical imaging is a significant issue, as it can result in the progression of kidney diseases, which can lead to renal failure, the need for dialysis, or even kidney transplantation. Furthermore, patients with kidney diseases often face challenges in tracking their progress due to the limitations of current monitoring methods. Blood tests, urine analysis, and blood pressure monitoring can provide valuable information, but they may not capture changes in the structure and function of the kidneys over time. This can make it difficult for patients to make informed decisions about their treatment options and manage their condition effectively. Without proper monitoring of their kidney function, patients may be at risk of worsening kidney disease, which can lead to serious complications and negatively impact their quality of life.

In summary, the potential for errors in traditional methods of analyzing medical images for kidney health and the limitations of current monitoring methods are serious issues that can have significant consequences for patients with kidney diseases. It is crucial to address these problems to improve the diagnosis and management of kidney diseases and ultimately improve patient outcomes.

3 OBJECTIVES

3.1 Main Objectives

The primary objective of this component is to diagnose kidney patients using medical images and image processing. The app will identify whether the patient is having a specific kidney disease or not. This component enables faster and more accurate diagnoses, leading to better patient outcomes.

3.2 Specific Objectives

- Diagnose the patient, analyze X-ray, MRI, ultrasound images, or all the above provided by the patient through image processing algorithms.
- Using multimodal image fusion to analyze different types of medical images at once to get a more accurate diagnosis.

- Create a visual representation of the progression of kidney disease over time that is easy to understand. This could include developing a timeline or graph that shows how the disease has progressed and how it is likely to progress in the future, as well as any potential treatments or interventions that may be necessary.
- Optimizing the image processing algorithms to reduce the computational requirements while maintaining a high level of accuracy in the diagnosis.
- Using cloud-based or server-based processing to offload some of the computational burden from the mobile device.
- Implementing compression techniques to reduce the size of the medical images, making them easier to transmit and process on the mobile device.
- Developing an efficient caching mechanism that stores previously processed images on the device so that they do not need to be reprocessed every time they are viewed.

4 METHODOLOGY

4.1 System Architecture

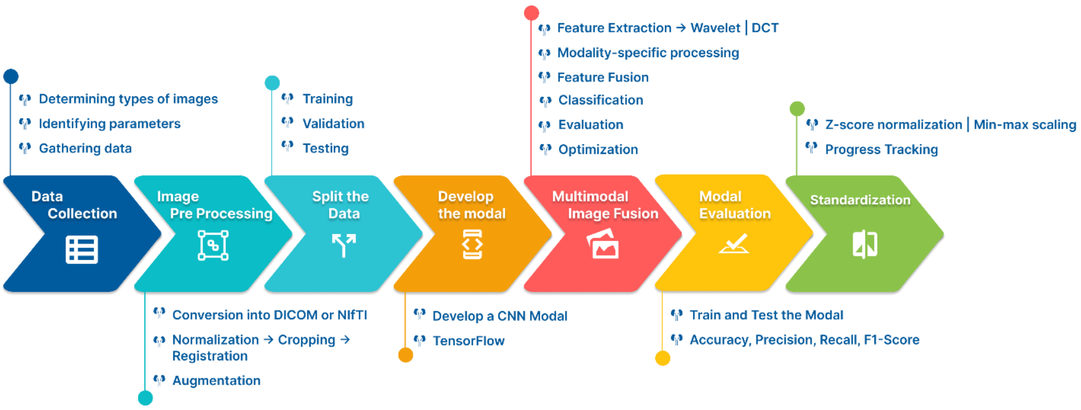

Figure 1:Component Architecture Diagram

The first step in this process is to collect medical images and labels from reliable sources such as medical institutions or public datasets. Once the images are gathered, they need to be preprocessed by converting them to a standardized format such as DICOM or NIfTI and applying preprocessing techniques such as normalization and image registration to ensure consistency across the dataset. Next, a CNN model needs to be developed using an appropriate architecture such as VGG, ResNet, or Inception and trained on the preprocessed images using dropout, batch normalization, or regularization techniques. The model's performance is evaluated on a testing set using metrics such as accuracy, precision, recall, or F1-score. To enable multimodal image fusion, the extracted features from each input modality are combined using fusion techniques such as weighted average or PCA and used for classification tasks such as detecting abnormalities in medical images. The performance of the multimodal image fusion approach is evaluated using metrics such as accuracy, sensitivity, specificity, and the area under the ROC curve. The next step is to develop a mobile app that allows users to upload medical images and track their progress in kidney health. The app should include features such as image upload, progress tracking, and results display and be designed with a user-friendly interface using frameworks such as React Native. The back-end functionality of the app should include data processing, model inference, and output generation. Standardization is essential in this process, as it ensures consistency between the training data and user-uploaded images. The appropriate standardization method, such as z-score normalization or min-max scaling, needs to be implemented within the app.

4.2 Commercialization of the Product

1. **Develop a comprehensive marketing strategy:** The first step would be to develop a marketing strategy that targets kidney patients and those at risk of kidney disease. This could involve promoting the app on social media, targeted advertising, and outreach to health organizations and medical professionals.
2. **Launch the mobile app:** Once the marketing strategy is in place, launch the mobile app on both the App Store and Google Play Store. Ensure that the app is user-friendly and that features such as the risk prediction tool, image analysis, and water quality measurement device are easy to use.
3. **Offer a free trial:** To encourage users to try out the app and see its value, offer a 30-day free trial with access to all features. During the trial period, users can evaluate the app and decide whether to continue using it by purchasing a subscription. Consider offering incentives to users who subscribe after the free trial, such as a discounted subscription price or additional features not included in the trial version.
4. **Partner with healthcare providers:** Partner with healthcare providers such as hospitals and clinics to offer our app as a resource for their patients. We could also consider partnering with healthcare insurance providers to offer the app as part of their member benefits.
5. **Collect and analyze data:** Collect data from app users to identify patterns and trends in kidney disease prevalence and risk factors. Use this data to improve the app's features and functionality and to develop targeted marketing campaigns.

5 SOFTWARE / HARDWARE METHODOLOGY

5.1 Software methodology

Requirements Gathering and Analysis:

Gather the requirements for the mobile app, including the type of medical images to be used, the diagnostic algorithm to be developed, and the necessary functionality. Analyze the requirements to determine the scope of the project.

Technology Selection:

Select the appropriate technologies for developing the mobile app, including React Native for the front-end, Node.js for the back end, MongoDB for data storage, OpenCV for image processing, TensorFlow for machine learning, and CNN for the diagnostic algorithm.

Agile Sprint Planning:

Break down the project into sprints that last 1-2 weeks. During the planning phase of each sprint, prioritize the development tasks, assign them to team members, and estimate the time required for each task.

Agile Sprint Execution:

During each sprint, the development team will work on the tasks assigned to them. Team members will collaborate, share progress, and work towards the sprint goal. Continuous integration and testing will be used to ensure that the app is functioning correctly and meets the requirements.

Agile Sprint Review:

At the end of each sprint, review the work completed during the sprint and demonstrate any new features or functionality to stakeholders. Gather feedback and identify areas for improvement.

Agile Sprint Retrospective:

Reflect on the sprint and identify what went well, what didn't go well, and what can be improved for the next sprint. Implement changes to improve the development process.

Deployment and Maintenance:

Once the development is complete, deploy the mobile app to the app store and ensure that it is running smoothly. Provide ongoing maintenance and support for the app, including bug fixes and updates as necessary.

Quality Assurance:

Throughout the development process, perform quality assurance to ensure that the app meets the necessary standards for medical applications. This includes ensuring that the diagnostic algorithm is accurate and reliable, and that the app adheres to relevant medical regulations.

Incorporate the use of Standardization and Multimodal image fusion techniques in the OpenCV image processing pipeline. The use of agile methodology will allow for flexibility and adaptability in the development process, making it well-suited for the changing requirements of the project.

5.2 Tools and Technologies

React Native: React Native can be used to develop a mobile app that can run on both iOS and Android platforms. The app can be designed to collect patient information, display health advice and recommendations, and provide access to the payment gateway.

NodeJS: NodeJS can be used to develop the backend APIs that the mobile app will interact with. The APIs can be used to process patient data, retrieve the GFR value, run machine learning algorithms, and provide the recommended health advice and treatment options.

TensorFlow: TensorFlow can be used to develop machine learning models that analyze patient data and categorize them into safe, cautious, or danger zones. The models can be trained to provide personalized recommendations based on the patient's specific health conditions and medical history.

MongoDB: MongoDB can be used to store patient information and health data. The database can be used to securely store patient information, and the data can be accessed by machine learning algorithms and backend APIs.

AWS: AWS can be used to host the backend APIs and machine learning models. AWS provides a secure and scalable platform for hosting these components, which ensures that the app can handle a large number of users and requests.

And most importantly, the CNN algorithm will be used to analyze medical images and identify patterns and features for accurate diagnosis, while multimodal image fusion techniques will be used to combine information from different medical imaging modalities to improve the overall accuracy of the diagnostic algorithm.

Possible image fusion algorithms would be considered:

Wavelet-based image fusion: This algorithm is commonly used for fusing medical images, as it can effectively preserve the relevant features in the images while reducing noise and artifacts. It works by decomposing the images into different frequency bands using a wavelet transform and then fusing the corresponding bands from the input images.

Intensity-hue-saturation (IHS) transform: This algorithm is particularly useful for fusing images that have different spectral resolutions, such as multispectral medical images. It works by converting the input images into the IHS color space and then fusing the intensity, hue, and saturation components separately.

Principal component analysis (PCA)-based image fusion: This algorithm is based on the idea of extracting the principal components from the input images and then fusing them based on their relative importance. It can be useful for fusing medical images that have different contrast or brightness levels.

Non-negative matrix factorization (NMF)-based image fusion: This algorithm is based on the idea of decomposing the input images into non-negative components and then fusing them based on their statistical properties. It can be useful for fusing medical images that have different spatial or temporal resolutions.

If the user wants to track their kidney health progress over time by uploading medical images periodically, it is important to ensure that the images are standardized and consistent across different time points. Standardization methods can help ensure that the images are comparable and can be used to monitor changes in the kidney health over time.

Standardization methods that can be used:

Image normalization: This method involves adjusting the brightness and contrast of the images to a standard level, which can help to reduce the variability in the images due to differences in lighting conditions or image acquisition parameters.

Image registration: This method involves aligning the images to a common reference frame, which can help to compensate for any differences in patient positioning or image acquisition parameters. Image registration can also help to identify any changes in the kidney structure or function over time.

Region-of-interest (ROI) analysis: This method involves selecting a specific area of the image that corresponds to the kidney, and then measuring specific features such as the size, shape, or texture of the ROI. ROI analysis can help to track changes in the kidney structure or function over time and can also be used to compare the results with normative values.

Quantitative analysis: This method involves using advanced image processing techniques to extract quantitative features from the images, such as the kidney volume, glomerular filtration rate (GFR), or other biomarkers of kidney health. Quantitative analysis can provide more accurate and objective measurements of kidney health and can also be used to monitor changes over time.

6 DESCRIPTIONS OF PERSONAL AND FACILITIES

Table 1-Description of personal facilities

Member	Component	Tasks
Marasinghe M.M.K. L	Kidney disease diagnosis using Image Processing	Collect and curate a large dataset of kidney images for training and testing machine learning models. Choose and configure a deep learning framework (such as TensorFlow) and develop a neural network architecture that incorporates CNN, multimodal image fusion, and standardization techniques. Train and optimize the neural network model using the collected dataset and appropriate machine learning algorithms and techniques (such as transfer learning, data augmentation, and hyperparameter tuning). Develop a mobile app user interface that allows users to upload images, view diagnostic results, and track their kidney condition progress over time. Implement the machine learning model in the mobile app, using appropriate libraries and frameworks to integrate with the mobile platform (such as Core ML for iOS or TensorFlow Lite for Android). Test and validate the mobile app and machine learning model through a variety of scenarios and edge cases, and fine-tune the model and app as necessary. Deploy the mobile app to the appropriate app stores and market the app to relevant audiences, such as kidney patients, doctors, and healthcare professionals. Continuously monitor and improve the app and machine learning model over time, incorporating user feedback and new research developments in the field of kidney diagnosis and treatment.

7 BUDGET AND BUDGET JUSTIFICATION

Resources	Estimated Price (LKR)
Cloud server host	25,000.00
Travelling	10,000.00
Internet	5,000.00
Stationery	2,000.00
Hardware parts/Sensors	15,000.00
Total	**57,000.00**

Table 2-Expected Expenditure

The proposed budget total cost amount is LKR 57000. To cover this expenditure, our group plans to collect funds from group members. The budget table should detail all the project expenses, including any necessary equipment, materials, or services required to complete the project. These costs might change in the future due to unforeseen circumstances or unexpected expenses, but with a clear budget plan and contributions from group members, the project can be completed successfully.

8 GANTT CHART

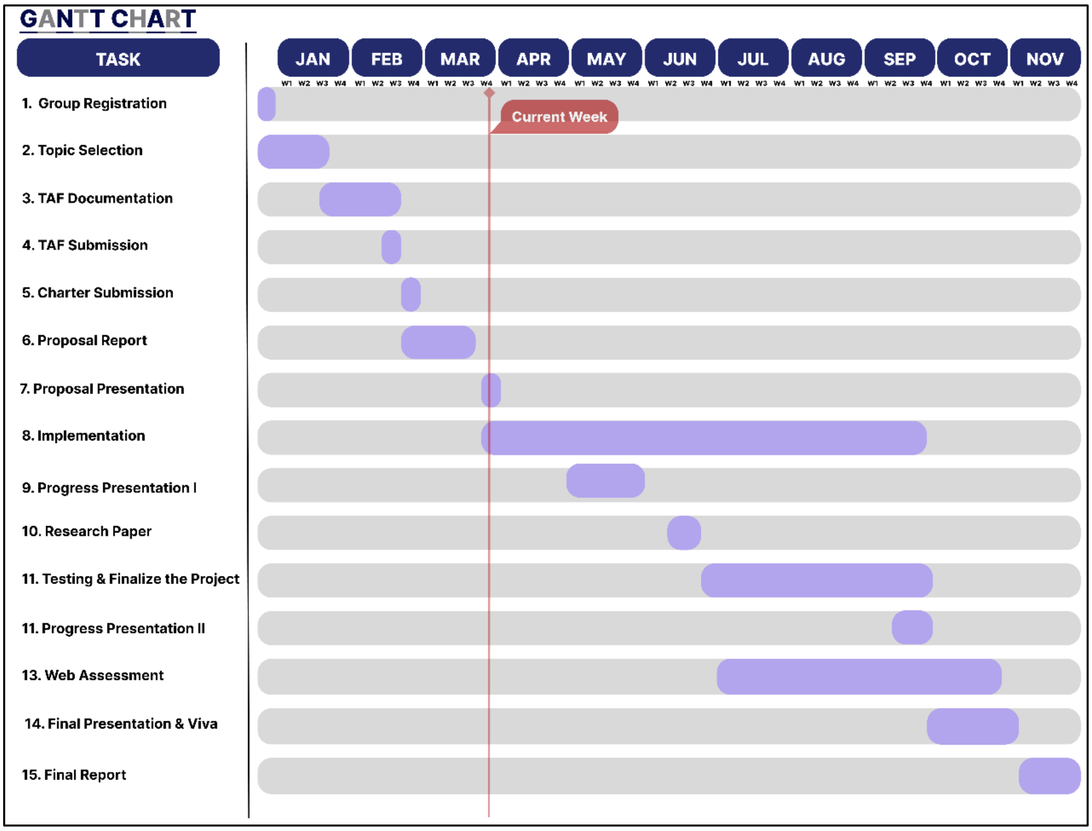

Figure 2:Proposed Gantt Chart

The Gantt chart above represents our proposed plan for the research project, with a focus on my component. We have made progress from January until this week, which is indicated by the green color. The remaining tasks are in purple, which we plan to complete in the coming months.

This Gantt chart is an essential tool for our research plan, as it helps us manage our time and resources effectively. It shows the timelines for each task, the dependencies between them, and the overall project schedule.

9 WORK BREAKDOWN CHART

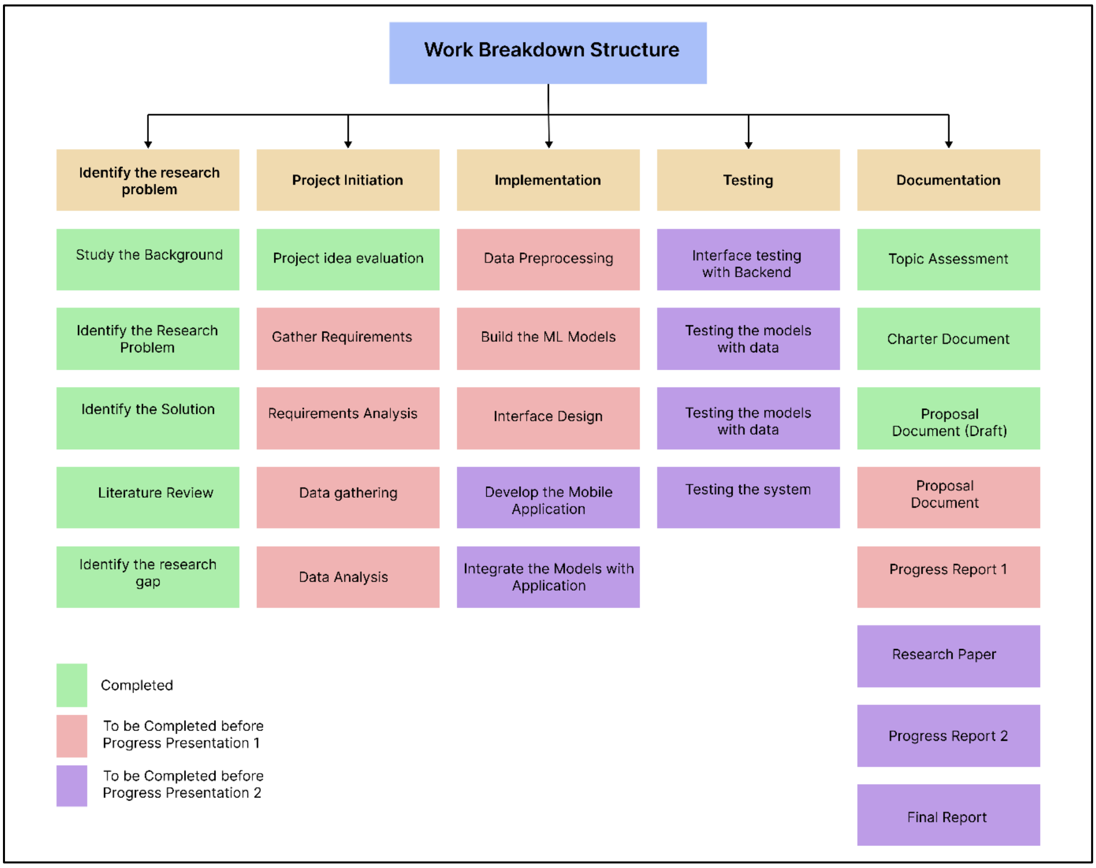

Figure 3:Work-Breakdown Structure

The work-breakdown structure for this project comprises five stages: the identification of the research problem, the initial stage, implementation, testing, and documentation. In the first stage, the research problem will be identified and analyzed thoroughly to develop a comprehensive understanding of the project's objectives and requirements. The initial stage will focus on designing the hardware and software components of the IoT-based water quality monitoring system. The implementation stage will involve developing the IoT infrastructure and integrating it with the ML algorithms for water quality prediction. The testing stage will be used to evaluate the performance of the system using pre-tested water samples and optimizing the algorithms for better results. Then, Integrate with the mobile application dashboard. Finally, the documentation stage will involve preparing comprehensive documentation of the project, including technical specifications, user manuals, and the project report.

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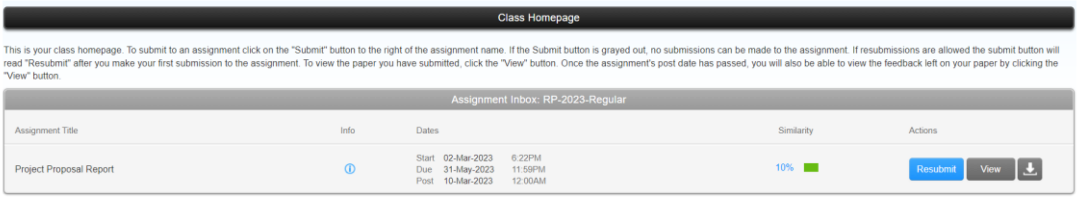
11 APPENDIX



Class Homepage
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