A REAL TIME NON-DESTRUCTIVE AUGMENTED REALITY BASED MOBILE APPLICATION FOR ASSURING THE QUALITY OF RAW MEAT ITEMS

Bachelor of Science (Computer Science)

Session (2021-2025)

Submitted By:

AYESHA MUNAWAR	2125110012
GHANIA SHAHZAD	2125110018
RAEESA ASIF	2125110046
SHIFA ZAHRA	2125110056

SUPERVISOR

Dr. Mariam Nosheen

Assistant Professor

DEPARTMENT OF COMPUTER SCIENCE

LAHORE COLLEGE FOR WOMEN UNIVERSITY, LAHORE

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A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items

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By

Ayesha Munawar	2125110012
Ghania Shahzad	2125110018
Raeesa Asif	2125110046
Shifa Zahra	2125110056

Dr. Mariam Nosheen Supervisor Department of Computer Science	*Prof. Dr. Muhammad Abuzar Fahiem* Chairperson Department of Computer Science

CERTIFICATE

BY THE PROJECT SUPERVISOR

I certify that the contents and form of project submitted by Ayesha Munawar, 12. 2125110012; Ghania Shahzad, 18. 2125110018; Raeesa Asif, 46. 2125110046; Shifa Zahra, 56. 2125110056 has been found satisfactory and according to the prescribed format. I recommend that it be processed for evaluation by the External Examiner for the award of degree in Bachelor of Science (Computer Science).

Supervisor

Signature: ____________________

Name: Dr. Mariam Nosheen

Designation: Assistant Professor


بسم الله الرحمن الرحيم

DEDICATION

This project is dedicated to our parents whose proficient guidance and splendid inspiration had positively influenced our lives and made us capable of attaining this degree successfully.

ACKNOWLEDGEMENT

We would like to acknowledge the efforts of all those people who have been involved in one way or the other in the completion of our project. First of all, we are very much grateful to **ALMIGHTY ALLAH** for giving us the opportunity and courage to complete this project successfully and helping us every step of the way. We would like to thank our family for having faith in us providing us with all the support and good wishes and always taking our side whenever we needed them the most. We wish to express our sincere gratitude to the Computer Science Department of Lahore College for Women University, Lahore, for providing us with the opportunity to work on the project titled *"A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items"*

We are also thankful to our very supportive and helpful internal advisor **Dr. Mariam Nosheen** who guided and encouraged us in carrying out this project work and everything that we needed to know about project studies throughout the project. Finally, we would like to thank our prestigious University (LCWU) that gave us the opportunity, confidence and guidance for the successful accomplishment of our project.

ABSTRACT

Meat quality is tightly related to human life. It is the most critical aspect for consumers to consider when purchasing such items. Few consumers are even willing to pay a higher price to guarantee the quality of meat. Developing countries (i.e. Pakistan) where majority consumers are below the poverty line cannot be able to afford meat items regularly. Moreover, lack of education, inadequate implementation of laws makes it difficult for them to estimate the quality of such expensive product.

The variability of raw meat items quality is one of the factors effecting the estimation of its quality. In literature, destructive and non-destructive approaches have been adopted. These techniques use sensory approach, laboratory equipment, human and machine resources that need time and human effort. To reduce the cost and enhance the portability of these techniques. The proposed project provides an android based mobile application have been developed that assures the quality of raw meat items. The system consists of five major modules (i.e. Mobile Application, Image processing, Raw meat item type classification, Raw meat quality classification, Raw meat quality assurance estimation and Augmented reality based report generation). For estimation and classification deep learning based hybrid model is developed with the accuracy of 93% as compare to (FastCNN (85%) and Resnet model (92%)). Total 1000 customized images for three meat types (i.e. beef, chicken, and fish) have been gathered from two sources (i.e. kaggle, Retailer). This system not only facilitates local vendors but also facilitate government authorities i.e. food authorities in assuring the raw meat quality items. This project also provides a foundational framework for future research in real time non-destructive augmented reality based mobile application for assuring the quality of raw meat items.

PREFACE

The basic purpose of this section is to provide a summary of this report. The documentation section was divided into the following SDLC (Software Development Life Cycle) phases:

- Introduction
- Background Literature
- Project Management Plan
- Software Requirement Specification
- Software Design Specification
- Proposed Work
- Software Test Specification
- Conclusion, Future enhancement, and Limitations
- References

Every phase has its significance according to the **"A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items"** project. This documentation facilitates those who want to know the development processes, tools, methodologies, and technicalities used for the development of this project.

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LIST OF ABBREVIATIONS

Sr. No.	Abbreviations	Description
1.	PMP	Project Management Plan
2.	SRS	Software Requirement Specification
3.	RMMM Plan	Risk Mitigation Monitoring Management
4.	FTR	Formal Technical Review
5.	SDS	Software Design Specification
6.	STS	Software Test Specification
7.	UC	Use Case
8.	UI	User Interface

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Part I

Introduction

This part covers the following topics:

- **Overview**
- **Motivational Factors**
- **Problem Statement**
- **Scope**
- **Proposed System Architecture**

1. INTRODUCTION

This chapter provides the introduction about the proposed project entitled as "A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items" have been discussed. The whole chapter is decomposed into five major sections. The first section elaborates the overview and need of this project. In the second section proposed idea motivational factors have been discussed. The third and fourth sections present the problem statement and scone of the proposed idea respectively. The last section presents the architectural view of the proposed idea.

1.1 OVERVIEW

The technological advancement in food industry and growing trends of economy, changes the consumption concepts of raw meat items [1]. Today it is available in many categories such as poultry, livestock, seafood etc. The global statistics of meat consumption over past few years that people consume it in their daily routine life for fulfilling their nutritional needs [2]. According to the Organization for Economic Co-operation and Development (OECD) meat consumption is expected to increase per person to 35.5 kg by the end of year 2024. The demand for quality meat items not only enhances the life style of their consumer's health but also facilitate them economically [3].

Figure 1.1: Visual differences in meat texture and color [5]

The quality of meat items are directly related to the survival and development of human beings, and it is the most critical aspect for consumers to consider when purchasing such items. Few consumers are even willing to pay a higher price to guarantee the quality of meat .Developing countries (i.e. Pakistan) where majority consumers are below the poverty line cannot be able to afford meat items regularly. Moreover, lack of education, inadequate implementation of laws makes it difficult for them to estimate the quality of such expensive product. The variability of raw meat items quality is one of the factors effecting the estimation of its quality

(a) Livestock (i.e. Raw beef)

(b) Poultry (i.e. Raw chicken)

(c) Sea Food (i.e. Raw Fish)

Figure 1.2: Example of Different Type of Meat [6]

Currently two approaches have been used for estimating raw meat items quality [4]. First is destructive and second is non-destructive. In destructive approach meat quality has been measured using chemical component in laboratory based environment. This approach of estimating quality is much expensive as they require high human resources and machines [1]. Moreover after the analysis the meat item get destroyed and cannot be able to use for consumption. This approach also utilizes lengthy analysis which needs more than two to three days that is difficult for consumers to adopt [5].

In non-destructive approach traditionally spectroscopy, colorimetric and sensory based techniques have been used for estimating the physiological and biological feature of raw

Meat items. It is also a laboratory based evaluation which is more expensive and need expert resources for estimation. To overcome the above gaps an AI based mobile application is proposed for real time raw meat quality estimation by using non-destructive technique [6] .

The core objective of this project is to develop a smart mobile application that can classify raw meat images to assure the quality of meat. The system relies on a deep learning model trained on a customized dataset of labeled meat images to make accurate predictions. Once classified, the freshness information is integrated into an AR-based interface that overlays the result on the meat sample in real-time, enhancing usability and providing a seamless user experience. This eliminates the need for physical expertise or specialized equipment, empowering ordinary consumers and vendors to evaluate meat quality instantly.

The project focuses on three popular meat categories: beef, chicken, and fish. Each type exhibits unique physiological characteristics, such as fat, flesh and bone which are detectable through visual cues and computer vision techniques.

The methods used in the previous research paper worked with expensive equipment such as spectroscopic techniques and imaging techniques which do not provide the real time report of assuring the quality of meat .Moreover, the methods and techniques used in their proposed solution are inefficient, complex, and expensive [4, 8]. To overcome the above mentioned gaps proposed project is provide “A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items”

The basic modules of the application are mobile application manager, image processing, Raw Meat Item Type Classification , Meat Quality Classification , Meat Quality Estimation and AR based Report Generation. The proposed idea helps the Food Authority, consumers, and local vendors to real time assure the quality of meat and make better decisions for the future. This project facilitates the researchers to enhance this idea in the future.

1.2 MOTIVATIONAL FACTORS

The motivational factors for this project are:

1. In literature, majority studies have considered destructive method that lead to sample wastage often time-consuming, requiring complex preparation and lab analysis. This proposed project uses non-destructive approach that assure quality without alter or damaging the sample.
2. Majority studies in the existing literature classify on a single type of meat (e.g., beef or pork). In contrast, the proposed project aims to classify multiple meat types, including beef, chicken, and fish.
3. Numerous studies in literature are using laboratory based image which is very time consuming and less accessible. This project uses real-time images to assure the quality of

meat in a portable and an easily accessible way.

4. Traditional meat freshness evaluation lacks active consumer participation. The proposed project gives direct control to consumers, allowing them to visually assess meat quality.

1.3 PROBLEM STATEMENT

The traditional destructive method of assuring the quality of meat items are time consuming, less accessible and need expensive equipment resource (i.e. human, machine etc.) which is very difficult for common consumers to afford, to overcome the above gaps, proposed project is provide an efficient, portable and effective application using deep learning and computer vision techniques for non-destructive meat items for consumers where they can assure the quality of meat items.

1.4 SCOPE

The proposed project entitled as “A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items” is a client-server based android application. The basic modules of the project are

- **Mobile Application Manager:** The mobile app manager module provides an interface for the consumer where they capture the images of meat item (i.e. beef, chicken and fish) from the mobile camera. The acquired images are subsequently stored on the server for further processing. This module is also providing the consumers with AR-based report, which is allowing them to readily determine the quality of meat items.
- **Image Processing:** The image processing module analyse visual data captured using the user’s mobile device. It acquires the saved images from the server and then classified those images using computer vision technique (i.e.FastCNN). It is then save the finalized images to the server for further processing.

- **Raw Meat Item Type Classification:** This module extract the saved images from previous module and classify the various types of meat items (i.e. beef, chicken and fish) using deep learning technique (i.e. ResNet-50). At the end, this module saves the classified images into the server.
- **Raw Meat Quality Classification:** This module classify the quality factors (i.e. fat, flesh and bone) of raw meat items using deep learning technique(ResNet) and after meat quality classification, it send classified images to the meat quality assurance estimation module to estimate the meat quality level.
- **Raw Meat Quality Assurance Estimation:** Raw Meat Quality Assurance Estimation module assure the meat quality factors along with their metrics level(s) using AI based technique (i.e. fuzzy logic) and save the results to the server.
- **AR Based Report Generation:** This module generates a report to the user where he/she can get the quality of meat items in AR based view.

1.5 ARCHITECTURAL OVERVIEW

The architectural overview of the project "A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items" is described at:

1.5.1 Three Tier Architectural Diagram of the Proposed Project :

A high-level overview of the components and subsystems of the "A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items" is given in Figure 1.1. Below the detail of components is described with several other important aspects of the overall design.

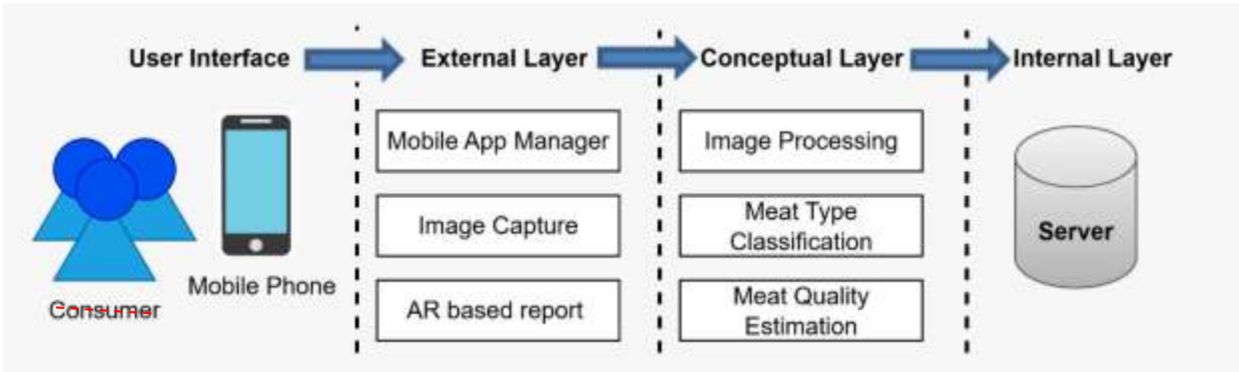

Figure 1.3: Three Tier Architectural Diagram of the Proposed Project

Part II

Background Literature

This part covers the following topics:

- **Literature Review**
- **Software Based Review**

2. BACKGROUND LITERATURE

This chapter provides a comprehensive overview of existing research and technological advancements relevant to the project, "A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items" .This chapter is divided into two main sections: Literature Review and Software-Based Review. Each section explores different approaches and methodologies that have been developed to address similar problems, highlighting their strengths, limitations, and relevance to this project.

2.1 Literature Review

The growing concern over food safety and quality has prompted researchers to explore advanced, non-destructive technologies for meat evaluation. Traditional manual inspection methods are time-consuming, subjective, and often unreliable. In contrast, recent developments in computer vision, spectroscopy, and sensor-based systems have demonstrated the potential to automate and enhance meat quality assessment with higher accuracy and consistency. This section presents a detailed review of existing literature focused on various methodologies and intelligent systems developed for meat quality detection. These studies provide critical insights into the technological landscape, highlighting strengths, research gaps, and areas that inform and support the development of our proposed real-time, AR-based mobile application for non-destructive meat quality estimation.

[1] Shao and Lan [1](2024) proposed a freshness indicator for seafood using a colorimetric film. The indicator changed color based on spoilage-related gases and was trained using a CNN classifier for accurate freshness prediction.

[3] Jo et al (2024) analyzed meat characteristics such as tenderness and marbling across various meats including beef, poultry, and pork. By employing spectral imaging systems, they showed improved accuracy in identifying spoilage and sensory degradation.

[4] Zaytsev (2024) presented an innovative combination of electronic nose sensors and RGB imaging for spoilage detection. Their approach relied on detecting gases such as ammonia and hydrogen sulfide, commonly produced during bacterial decomposition.

[5] Zhang (2023) designed a biosensor system for meat adulteration detection. Combining bio-nanotechnology and deep learning, the system could detect added non-meat fillers or changes in meat purity.

[6] Mileusnić et al. (2022) introduced a computer-assisted meat inspection tool that combined colorimetric sensors, PCA, and CNN models. This system provided rapid classification of freshness levels across various meat types.

[7]Wu et al. (2024) proposed an integrated approach using multiple non-destructive technologies to analyze meat quality across different types—beef, lamb, poultry, and mutton. Their research combined hyper spectral imaging, image processing, spectroscopy, and electronic nose systems to evaluate physiological and chemical meat properties such as pH, fat content, and oxidation level.

[8] Wegner (2024) utilized destructive laboratory techniques including NIR spectroscopy and conductivity measurements to study quality parameters like protein, collagen, and fat composition in guinea fowl meat. This study supported future work in converting such features into non-destructive indicators.

[9] Adenuga (2025) validated a real-time PCR method to identify meat authenticity in red deer using DNA sequences. The system demonstrated high accuracy and relevance for food safety and fraud detection in multi-origin meat products.

[10] De Smet (2024) examined the intersection of meat quality and sustainability, exploring how modeling tools can assess environmental impact while maintaining high nutritional quality in meat production.

[12] Elangovan (2024) applied convolutional neural networks in real-time meat environments, allowing beef and poultry quality to be assessed during processing. Their mobile-compatible model improved speed and on-site analysis.

[12] Holman (2021) reviewed traditional meat quality testing methods such as colorimetry, pH meters, and mechanical texture analyzers. While effective, these methods required laboratory settings and human supervision.

[13] Bulgaru (2022) analyzed the impact of dry aging on beef tenderness and juiciness. Their sensory studies were correlated with moisture loss, muscle fiber breakdown, and enzymatic activity using standard laboratory tools.

[14] Ngongoni (2025) evaluated the preservation effects of polyphenols in ground beef. Their study showed how antioxidant-rich additives could reduce lipid oxidation and improve shelf life without altering meat flavor.

[15] Kurniawati (2024) developed an AI-based model focused on halal meat logistics and quality preservation. CNN models were used to predict freshness levels and spoilage probability for poultry and beef in halal-certified supply chains.

[16] Liu and Jiang (2024) explored the integration of augmented reality (AR) and AI for food quality assessment. Their work demonstrated real-time interaction using mobile phones to visualize the freshness of meat products.

[14] Shao (2024) further expanded the application of colorimetric freshness indicators in aquatic products, using visual gas sensors paired with CNNs to monitor spoilage. The system could classify freshness in real time.

[15] Hou (2025) developed the YOLO-shrimp model using CNNs for seafood classification.

It focused on shrimp but set a precedent for the classification of other seafood types using mobile-based vision systems.

[7] Weng (2025) studied the effects of dietary supplements on meat quality. By analyzing amino acid levels and muscle growth markers, their study contributed to understanding how nutrition influences meat tenderness and texture.

In conclusion, the reviewed literature highlights significant progress in applying non-destructive technologies such as computer vision, spectroscopy, and deep learning for meat quality assessment. However, many existing solutions remain limited in portability, real-time usability, and practical deployment, especially for end-users like consumers or small retailers. This gap emphasizes the need for a user-friendly, intelligent mobile solution that ensures accuracy while reducing dependency on traditional, time-consuming methods. Building on the strengths and limitations identified in previous studies, the proposed project aims to deliver a real-time, AR-based mobile application that integrates modern CV and DL techniques to automate meat quality inspection efficiently and accessibly.

A tabular review of literature relevant to meat quality assessment is provided in Appendix A.

.2.2 Software Based Solutions

In parallel with advancements in hardware and sensor-based technologies, software-driven approaches have played a crucial role in real time meat quality assessment. Recent studies have demonstrated the effectiveness of artificial intelligence (AI), deep learning (DL), and computer vision (CV) algorithms in detecting visual cues such as discoloration, marbling, texture irregularities, and structural defects in meat products. Mobile applications, lightweight CNN architectures, and integrated AR tools are increasingly being explored to offer real-time, non-destructive solutions. This section presents a comprehensive analysis of software-based techniques, tools, and systems that contribute to enhancing the reliability and efficiency of meat inspection processes.

[1] W et al. (2024) developed an integrated software framework combining non-destructive sensing techniques and deep learning models to assess meat quality. The system relied on hyper spectral imaging and spectroscopic analysis to evaluate physiological parameters like pH, texture, marbling, and fat distribution in beef, poultry, and lamb. Their implementation used computer vision libraries to extract pixel-level information and classify meat conditions into quality grades. The model architecture included a CNN-based classifier with optimized layers trained on a multispectral dataset. Their platform demonstrated real-time applicability, pushing the boundaries of mobile-compatible meat analysis.

[2] Zhou (2024) introduced a novel software prototype to estimate collagen concentration in beef using fluorescence spectroscopy. The system comprised a 3D camera-based imaging setup coupled with a nano-LED light source and CMOS sensor. A custom machine learning classifier was trained on images displaying collagen fluorescence and oxidative properties to classify meat into different freshness levels. The application integrated OpenCV and TensorFlow-based modules to enable real-time feedback on mobile screens. Their contribution advanced portable meat quality assessment with high precision in identifying degradation stages.

[3] Jo (2024) designed a spectral image analysis system using deep convolutional networks to classify meat tenderness, juiciness, and color variation. They trained their models on datasets

comprising beef, poultry, and pork cuts, capturing pixel-level variations in muscle texture and fat streaks. The software backend leveraged PyTorch for model training, and the frontend enabled real-time detection using mobile cameras. Their work stands out for addressing tenderness prediction, which is less explored in AI-based systems.

[4] Zaytsev (2024) combined RGB image analysis with gas sensor inputs to develop a real-time spoilage detection platform. Their e-nose system used metal oxide sensors to detect ammonia, hydrogen sulfide, and volatile organic compounds associated with meat decomposition. This data was fed into a hybrid CNN-RNN model for classifying freshness levels. The integration of sensory data into a computer vision pipeline made their software robust against visual-only limitations and improved prediction under varying lighting and temperature conditions.

[5] Zhang (2023) introduced a multimodal AI platform combining biosensor readings, spectral imaging, and neural networks for detecting adulteration and spoilage in meat. The software integrated inputs from fatty acid sensors, visual marbling patterns, and microbial activity to build a unified classifier using ensemble learning. With cloud support, the tool could analyze images and sensor data from remote slaughterhouses or markets, making it valuable in distributed food systems.

[9] Wegner (2024) employed destructive methods like NIR spectroscopy and conductivity measurements to quantify water-holding capacity, tenderness, and protein content in guinea fowl meat. Though not fully software-based, the results were used to simulate non-destructive prediction models. The study produced a synthetic dataset that future computer vision systems can use for model training. The data was preprocessed using MATLAB, and regression models were implemented in Python for estimating quality based on synthetic imaging features.

[10] Adenuga (2025) contributed to species authentication in meat through real-time PCR-based DNA recognition software. The system was designed to run high-throughput DNA sequence comparison using bioinformatics tools, ensuring meat traceability in red deer products. Though initially developed for labs, the underlying algorithms were adaptable to mobile applications, particularly those using DL models trained on genomic sequences. This offered a hybrid pathway between biological and visual inspection.

[11] De Smet (2024) presented a model that combined sustainability metrics with nutritional profiling of meat. Their software simulated environmental impact (carbon emissions, water use) and cross-referenced this data with meat quality characteristics like fat content and amino acid profiles. This simulation engine can be integrated into AI platforms to support quality tracing across the supply chain. They also proposed an API interface that could link with mobile inspection tools to visualize sustainable meat quality rankings.

[12] Elangovan (2024) implemented an ensemble CNN architecture composed of ConvNet-18 and ConvNet-24 for real-time beef and poultry quality classification. Their system operated on a Raspberry Pi device connected to a standard webcam, running lightweight Tensor Flow models. The classifier achieved over 90% accuracy in differentiating between fresh, stale, and spoiled meat. The software was optimized for edge computing and embedded systems, enabling deployment in mobile applications and IoT devices.

[13] Holman (2021) provided a critical review of traditional lab-based meat evaluation systems and highlighted their limitations in modern supply chains. Although primarily descriptive, their analysis enabled the construction of simulated datasets that computer vision researchers later used to replicate meat color and texture transitions using DL models. These simulations served as ground truth benchmarks in recent software-based meat evaluation systems.

[14] Bulgaru (2022) presented a software tool for tracking dry-aging effects on beef. The system used visual texture analysis algorithms to monitor surface darkening, fat yellowing, and water loss across 3, 7, 14, and 28-day intervals. A logistic regression model was used for spoilage prediction, and a web dashboard provided a visualization interface for butchers and retail chains to manage product aging timelines.

[15] Ngongoni (2025) developed a software module that simulated oxidation processes in meat treated with natural polyphenols. By tracking light reflectance and color change, the application could estimate antioxidant effectiveness and predict shelf life. Their platform supported integration with image classification tools to verify spoilage levels in preserved meat products.

[16] Kurniawati (2024) built a CNN-based system for halal meat freshness and logistics monitoring. The tool was trained on a proprietary dataset of over 5,000 poultry and beef images and integrated with supply chain software to flag meat nearing spoilage. They developed a mobile version of the platform compatible with Android OS, complete with OCR and barcode scanning for verifying halal certifications.

[17] Shao and Lan (2024) developed freshness indicators using pH-sensitive films embedded with AI-driven visual recognition software. Their system captured real-time color changes in seafood products and used a CNN classifier to interpret spoilage progression. The model was deployed in a cross-platform mobile application, which utilized augmented reality overlays to inform users of freshness levels. Their system was particularly efficient in low-light scenarios due to brightness normalization algorithms.

[18] Gongshuai (2024) developed an LSTM-based classifier for temporal meat freshness prediction. Their model used visual time-series data, including fat brightness and moisture sheen, to classify beef freshness over time. Their interface used animated heat maps to visualize how

freshness changed across storage intervals, making it suitable for educational and industrial applications.

[19] Sanchez et al. (2022) focused on quantifying biogenic amines and lipid oxidation in pork and beef using hyper spectral imaging and deep learning. Their system extracted spectral features from meat images under controlled lighting and trained a multi-layer perceptron classifier to predict spoilage probability. The software emphasized freshness indicators such as histamine, cadaverine, and putrescine, using a custom Python-based UI to visualize the outputs. Their work bridged spectroscopy and AI, making quality classification accessible through cloud-based interfaces.

To conclude, the software-based review highlights the increasing reliance on intelligent systems that leverage deep learning and vision-based models for accurate, scalable, and portable meat quality prediction. Although many existing applications and frameworks show high accuracy in controlled environments, challenges remain in achieving real-time performance, generalization across different meat types, and user-friendly deployment. These insights strengthen the motivation for developing of proposed mobile-based system, which integrates AR visualization and lightweight CNN models to deliver an accessible, non-destructive, and efficient solution for real-time meat quality assurance.

A tabular review of current software-based solutions relevant to this domain is provided in Appendix B.

Part III

Project Management Plan

(PMP)

This part covers the following topics:

- **Project Definition**
- **Risk Plan**
- **Quality Plan**
- **Software Configuration Plan**
- **Resource Plan**
- **Infrastructure Plan**

3. Project Management Plan

This chapter provides a detailed project management plan, including the modeling approach, key milestones, and deliverable artifacts. It outlines the project's risk management plan, detailing the identification and mitigation of risks (RMMM).This chapter also discuss the quality plan, software configuration plan, and resource plan, which includes effort estimation, scheduling, team members, structure, roles, and responsibilities. Finally, the project describe the infrastructure plan, covering both the development and test environments.

3.1 Project Definition

3.1.1 Modeling Approach

For complex systems such as real-time meat quality assurance applications, selecting a structured development model is essential to manage multifaceted components like image analysis, machine learning integration, AR visualization, and mobile compatibility. In this case, the proposed project handles tasks ranging from image preprocessing and deep learning classification to real-time AR reporting, all of which demand modular, scalable, and adaptable planning. The idea is not only to optimize the meat quality detection process but to ensure robust performance, portability, and a user-friendly interface on mobile platforms.

The proposed project requires careful decomposition because it involves handling visual sensory data, classifying it through CNN models, and presenting real-time results to the user. Inspired by complex modeling approaches referenced in scientific literature related to vision-based quality assurance systems, a refined incremental model suited for AI-integrated mobile applications is adopted. This approach allows development in independent yet interdependent stages—

accommodating learning model iterations, user feedback, and feature expansion. In the *incremental model*, the Project Plan is introduced, Requirements Engineering, System Design and Module Workflow, Integration, Integration Testing, and deployment phase whose detailed description is given below. The model in Figure 3.1 which is used has the following steps: This model encompasses phases such as Project Planning, Requirements Engineering, System Design and Module Workflow, Integration, Integration Testing, and Deployment.

1. Project Plan
2. Requirements Engineering
3. System Design and Module Workflow
4. Integration
5. Integration Testing
6. Deployment

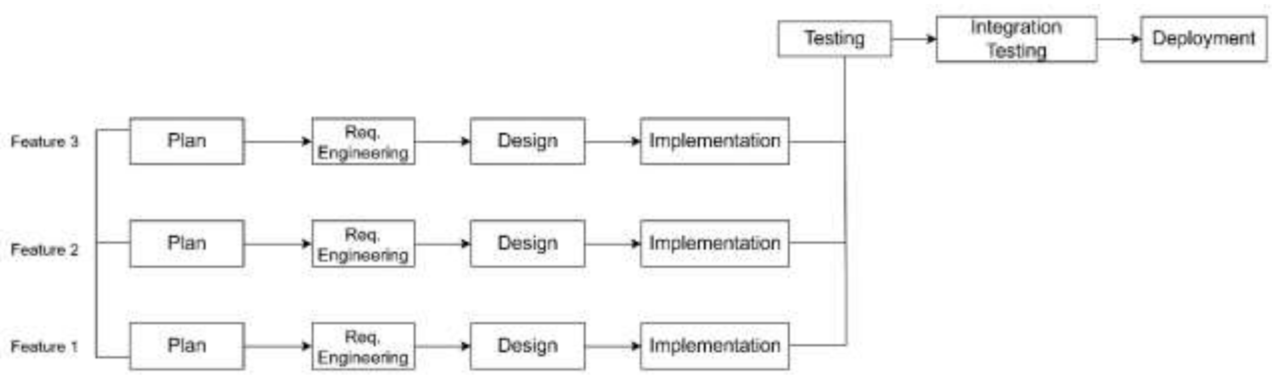

Figure 3.1: SDLC Model of the Project

A brief description of the above steps is discussed as follows:

1. Project Plan

This phase involved identifying the core problem, defining goals, conducting literature review, and discussing the resource requirements. It also addressed project scheduling, risk assessment, milestone tracking, and team structure. The project plan established a roadmap that includes supervision checkpoints, deliverable timelines, and defined collaboration tools.

2. Requirements Engineering

The requirements were gathered through a combination of academic research (from papers on meat quality detection), field observations, and discussions with end users such as meat retailers and food safety practitioners. The goal was to ensure that all real-world usability, performance, and regulatory compliance needs were captured. The output of this phase was the finalized Software Requirement Specification (SRS) document.

3. System Design and Module Workflow

To ensure structured development and clear progress tracking, the system is designed as a modular application with logically segmented functionalities. Rather than treating each feature as a standalone component, the application is developed through a unified workflow that allows individual features to be built in harmony with the overall system architecture.

The project is designed to follow a layered approach. It starts with the user interface layer, which handles user input, image capture, and display. This is followed by the processing layer, which includes image preprocessing, feature extraction, and deep learning-based classification. Lastly, the output layer manages result interpretation, augmented reality display, and report generation.

Each module in the system, such as image acquisition, meat quality detection, and AR reporting, is implemented in parallel with continuous integration. Instead of isolating each module, all functions are interlinked to ensure seamless data flow and system stability. During the development, continuous testing and refinement cycles are applied to each feature to maintain performance and usability.

This integrated and iterative approach helps simplify complex tasks while ensuring that the application evolves cohesively, minimizing risks associated with isolated development. It also facilitates better collaboration among team members, as each function progresses with full visibility into its role in the overall system.

5. Integration

All components when have been tested are combined to look at the complete project. Component Integration is again conducted in light of the project and component plan.

5. Integration Testing

The components are integrated to make up the system. This phase is concerned with finding errors that result from unanticipated interaction between components and components interface problems. It is also concerned with validating that the system meets its functional and non-functional requirements and testing the emergent system properties.

6. Deployment

The deployment phase involves preparing infrastructure and environments, verifying hardware, software, and network configurations. It includes developing a detailed deployment strategy with timelines, responsibilities, and risk assessments. The process focuses on version control, release management, and rigorous testing to ensure successful deployment. Post-deployment tasks include monitoring, maintenance, user training, support setup, and documentation updates for future reference.

3.1.2 External Milestones:

Sr. No.	Milestone	Deliverables/ Description/ Comments	Date
1	Project Proposal	The proposal defines the topic, establishes the scope required for completion, and estimates completion times for each stage of the work.	17th Jan 2025
2	Software Requirement Specification (SRS)	This document contains the requirements specifications and definitions for the Project software application. It includes all functional and non-functional requirements of the software, which are necessary for successful completion of the project.	17th March 2025
3	Software Project Management Plan (PMP)	PMP defines whole planning about management of the project.	17th Feb 2025
4	Software Design Specification (SDS)	SDS describes the whole design of the system by diagrams.	30th March 2025
5	Software Test Specification (STS)	Software Test Document describes different types of Testing adopted in the Project.	11th May 2025
6	Project Evaluation & Documentation	Demonstrate code and documents of the final project in the form of internal presentation.	1st week - July 2025

7	Evaluation	Demonstrate code and documents of the final project in the form of external presentation & submit hard binding documentation of whole project with code.	August 2025

Table 3.1: External Milestones

3.1.3 Deliverable Artifacts:

At the end of the project, the whole project documentation and software hard and soft copies will be submitted to the management of the university.

3.2 RISK PLAN

3.2.1 Risk Identification and RMMM Plan

Generally, three types of software risks might occur in the project:

- Cost Risk
- Performance Risks
- Schedule Risk

Sr. N0.	Risk Description	Probability	Mitigation plan	Monitoring	Management
1.	Requirements of the system are not fully understood by the project team.	Medium	Requirements are gathered from research papers	Check after regular intervals, the	View the results to make sure that the requirements are

				understanding of the team	clearly understood.
2.	The cost of this system may affect at the time of system deployment.	Medium	System must be delivered within due date.	Variation in prices must be noted down and checked periodically.	Meet the deadline by checking daily work.
3.	Tools for the deployment are not appropriate.	High	We can mitigate this risk by selecting appropriate tool for development.	Comparison of different results from different tools can help.	Provided and suggest the best tool.
4.	If meetings are not conducted regularly, working of the system may affect.	Medium	Meetings must be conducted regularly.	In each meeting ask the members for the assigned tasks.	Make sure that the tasks are completed within allotted time.
5.	The development team will not be able to complete the system within due date.	Medium	Advisor will distribute the time between different phases. This would help the developers	Proper time management is necessary. Proper checking and	Exclude the factors affecting the deadline of the project.

			to complete within due date.	accomplishment of tasks within due date is more important.	
7.	The cost of system may affect due to defective delivery.	Medium	Product must be delivered without any defects.	The product must be checked over and over again to make sure it is defect free.	Tested the product after regular intervals.
8.	During the construction the whole system may collapse. Cost and schedule may affect due to this risk.	High	There must be a backup of system.	Backup was created and date and time of the backup was noted.	Backup was kept and different places to make sure we don't lose any work.

Table 3.2: RMMM Plan

3.3 QUALITY PLAN

The Quality Plan outlines the standards, practices, resources, and procedures to ensure the delivery of a high-quality software project that aligns with the functional and non-functional requirements of the proposed project, *"A Real-Time Non-Destructive AR-Based Mobile*

Application for Assuring the Quality of Raw Meat Items." This project serves as a guideline for quality assurance activities during all phases of development.

To ensure accuracy and reliability, the project will incorporate both process-based and product-based quality measures. The software components will be evaluated through systematic reviews, validation strategies, and rigorous testing processes. Quality metrics will include performance, usability, reliability, maintainability, and portability.

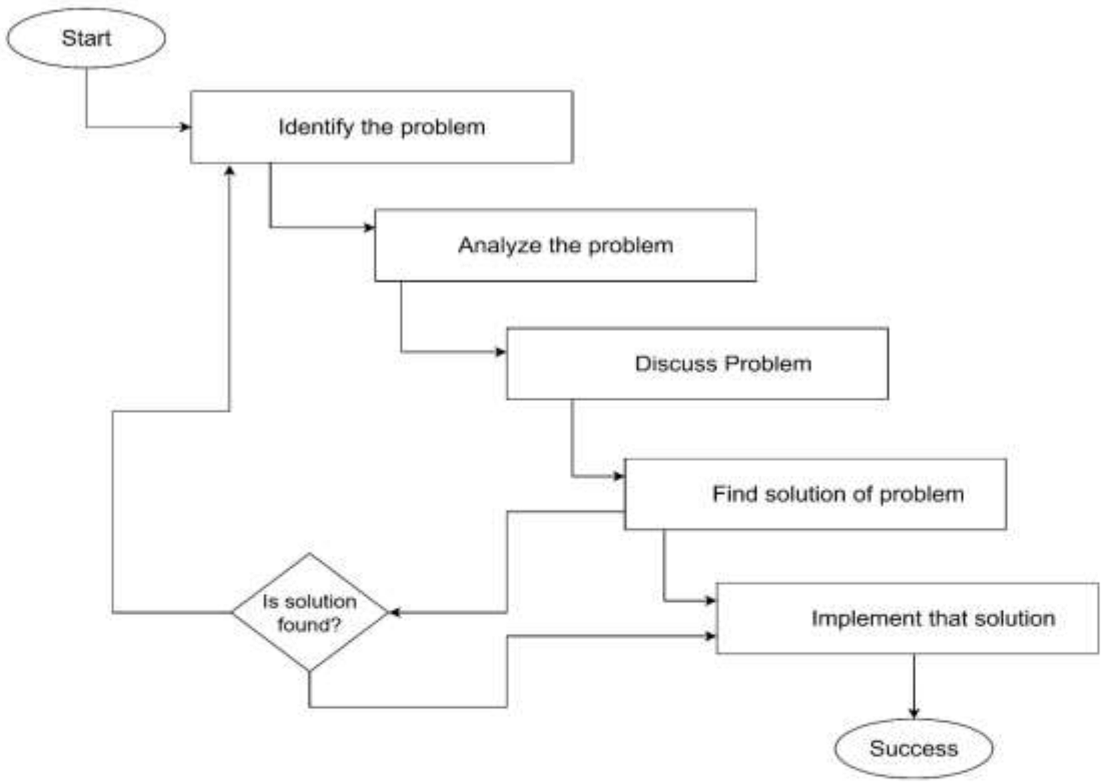

Figure 3.2: Software Quality Plan of Proposed Project

Key Elements of the Quality Plan

- **Quality Standards**: IEEE and ISO/IEC software engineering standards are followed to ensure consistency in design, implementation, and documentation.
- **Code Quality**: Code reviews, static analysis tools, and adherence to naming conventions and modularity principles are practiced throughout development.

- **Version Control**: Git-based version control is utilized to track changes, manage revisions, and ensure collaboration integrity.
- **Validation Techniques**: Unit testing, integration testing, and system testing is performed to verify correctness and functional compliance.
- **Documentation Quality**: All deliverables including SRS, design documents, user manuals, and reports are undergo proofreading and structured formatting.

This structured quality plan ensures that the developed mobile application meets stakeholder expectations, functions effectively in real-world environments, and maintains robustness throughout its lifecycle.

3.4 Software Configuration Plan

The Software Configuration Plan ensures the systematic management and control of the software environment throughout the project lifecycle. As illustrated in Figure 3.3, the process begins with determining the system requirements, which provides a foundational understanding of both hardware and software needs essential for effective configuration.

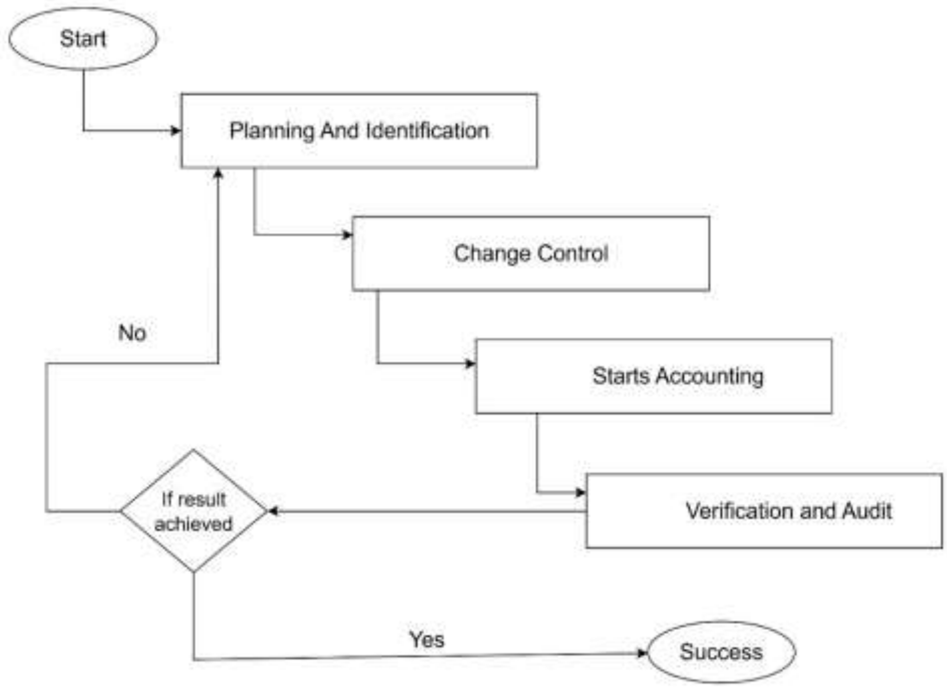

Figure 3.3: Software Configuration Plan of Proposed Project

Once the system requirements are outlined, the next step is to plan the configuration**.** This phase involves deciding the structure of configuration files, version control systems, and integration points with other system components. It sets the standards for configuration naming conventions, storage paths, and documentation practices.

Following the planning phase, the configuration is implemented by installing the necessary software, which includes the development tools, libraries, and runtime environments specified during requirement gathering. This installation must be consistent across all development and testing environments to ensure uniformity and reliability.

After installation, the final step is to perform thorough testing. This ensures that the system operates correctly within the configured environment. Testing validates the configuration, identifies any issues early in the lifecycle, and ensures the environment supports the functional and non-functional requirements of the application.

This plan is essential for maintaining consistency, traceability, and control throughout the development process.

3.5 RESOURCE PLAN

3.5.1 Effort Estimation

Work Breakdown Structure	**Resources**	**Days**
Requirement Gathering	4	5
Analysis	4	5
Project Proposal	4	8
Review	1	1
Software Requirement Specification	2	10
Review	1	2
Use Case Model	2	6
Review	1	2
Use Case Specification	2	6
Review	1	2
Software Design Specifications	2	10
Review	1	2
Project Management Plan	2	10

Review	1	1
Coding Review	2	9
Test Plan	2	9
Review	1	1
Deploy	4	4

Table 3.3: Project Effort Estimation

No. of Days = 4*5+4*5+4*8+1*1+2*10+1*2+2*6+1*2+2*6+1*2+2*10+1*1+2*10+1*1 +2*9+2*9+1*1+4*4

= 219 days

No. of Hours = 219*24= **5256 hrs.**

3.5.2 Schedule

Throughout the project, weekly meetings with be held with the team members and project supervisor.

3.5.3 Team Members

The project's team comprises of four members; designated for software development and documentation

3.5.4 Team Structure

The team has defined the leader coordinates all the tasks and other three members will manage all the related subtasks. All team members communicate directly with project coordinator and supervisor when needed.

3.5.5 Roles and Responsibilities

Project Coordinator: Coordinates to meet the deadline of schedule.

Development Team: Responsible for developing the system going through different phases of SDLC and making documentation of the system.

Supervisor: Responsible for advising the development team on difficult matters, helping to understand real-world needs, to make this project more valuable.

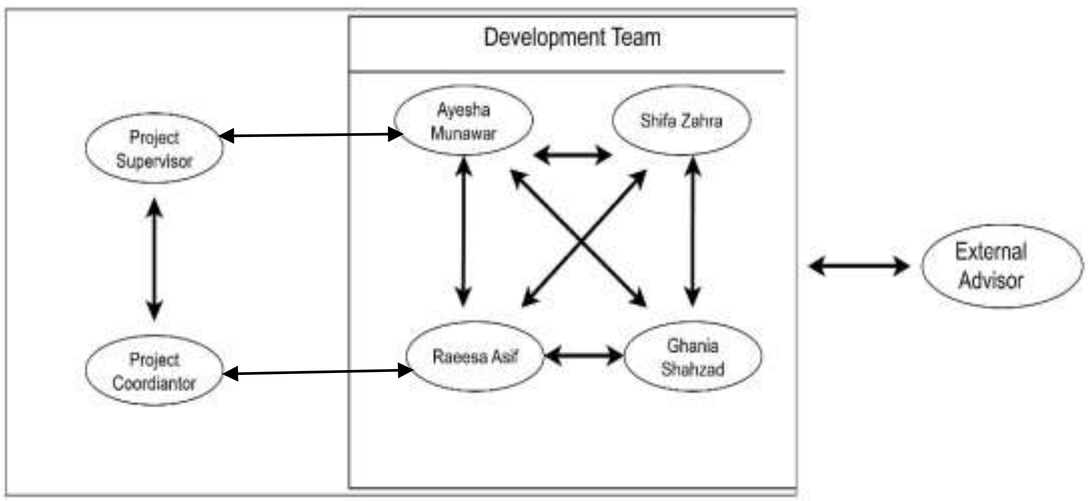

Figure 3.4: Team Structure of Proposed Project

3.6 INFRASTRUCTURE PLAN

3.6.1 Development Environment

The development environment consists of two parts:

i. Development machines

ii. Development tools

A description of these two parts is given below:

i. Development Machine

The tools required for the development of the app are

- ➢ Windows 10 64 bits
- ➢ 8GB of RAM
- ➢ At least one PC intel core i5
- ➢ Minimum 120 GB SSD

Android phone with:

- Octa-core processor
- Minimum 6 GB RAM.
- Storage: Minimum 128 GB of internal storage
- Display: Full HD (1080p) or higher resolution.
- Battery: Large capacity battery (4000 mAh or higher).
- Operating System: Android 14.0 (Pie) or higher.
- Connectivity Support for 4G/5GBluetooth and Wi-Fi

ii. Development Tools

Documentation

- ➢ Microsoft Office 2021
- ➢ Draw.io

Coding

- ➢ Python
- ➢ Deep Learning
- ➢ Open CV
- ➢ Tensor Flow
- ➢ Google Colab

Operating System

- Windows 10
- Android 14.0

3.6.2 Test Environment

Hardware Specifications

1. **Android Testing Devices**

   At least two Android smartphones

   - Different Android OS versions (i.e. 13 and 14)
   - RAM: Minimum 2 GB
   - Storage: Enough free space for installing and testing apps
   - Internet Connectivity: Wi-Fi and/or mobile data for testing network-related features

2. **PC**

- PC intel core i9
- Windows 10 64 bits
- 8GB of RAM
- Minimum 120 GB SSD

Testing Tools and Software

1. Android Debug Bridge (ADB)
2. Android Emulator
3. Automated Testing Frameworks
   - JUnit and Espresso
4. Performance Testing:
   - Android Profiler (included in Android Studio)

5. Bug Tracking and Management:

   - Jira and Trello

6. Google, Firefox Google Play Console

<u>Part IV</u>

Software Requirement Specification

(SRS)

This part covers the following topics:

- **General Description**
- **Specific Requirements**
- **Use Case Diagram**
- **Use Case Description**

4. Software Requirement Specification

This chapter introduces the software requirement specification (SRS) of proposed project mobile application. It provides a general description of the project functional and non-functional requirements, including its perspective, user characteristics, and general constraints.

4.1 GENERAL DESCRIPTION

4.1.1 Product Perspective

The proposed project, titled “A Real Time Non-Destructive Augmented Reality Based Mobile Application for Assuring the Quality of Raw Meat Items," is designed to facilitate food authorities, consumers and quality inspectors by providing a comprehensive platform for evaluating the quality of meat items. This application leverages smartphone camera technology to capture real-time images of raw meat items, which are then analyzed using advanced computer vision and deep learning techniques to determine their freshness and quality condition. The primary services offered by the application include:

- Meat Types Classification
- Meat Quality Estimation
- Report Generation

4.1.2 User Characteristics

The intended users of characteristics are:

- Local vendors may use the mobile app to check meat quality.
- Food Authority facilitate in assuring the raw meat quality items.
- Laboratory experts perform quality tests in food safety labs.

4.1.3 General Constraints

- The proposed project is designed to work on Android.
- A stable internet connection with a minimum speed of 1 Mbps is required for uploading images and for the smooth operation of the application.

4.2 SPECIFIC REQUIREMENTS

4.2.1 Functional Requirements

The functional requirements of the proposed project are:

- **Mobile App Manager**

  The mobile app manager provides as an interface for the consumer where they capture the meat item(s) images from the mobile camera.

- **Image Processing**

  The image processing module analyses visual data captured on the user's mobile device.

- **Meat Type Classification**

  The project automatically classify the meat as either Beef, Chicken, or Fish.

- **Real-Time Freshness Analysis**

  The proposed project analyze the uploaded image in real time to assess the freshness level of the meat.

- **Freshness Classification Output**

The project provide results in the form of freshness levels:

- Fresh
- Spoiled

- **Augmented Reality Overlay**

  The proposed project overlay the analysis result directly on the meat image using AR technology**,** highlighting key areas of concern.

- **Generate AR Report**

  The proposed project generate a downloadable report summarizing the freshness analysis for each meat sample.

4.2.2 Non-Functional Requirements

The functional requirements of the proposed project are:

- **Performance Requirements:**

The proposed project must perform efficiently, processing and analyzing uploaded data in a timely manner. This project provide analysis results within 3 to 5 seconds of uploading the meat sample

- **Platform Compatibility**

  The proposed project support:

  - Android (version 8 and above)

- **Compatibility:**

The proposed project must be compatible with various meat models and mobile devices running Android systems. It also support high-resolution image and video inputs for accurate analysis.

- **Reliability**

The proposed project ensuring consistent performance and accuracy in analysis and recommendations. Any downtime or failures must be minimized to maintain user trust and operational efficiency.

4.3 USE CASE DIAGRAM

Figure 4.1 shows the use case diagram for the "***Meat Quality Estimation*** ".

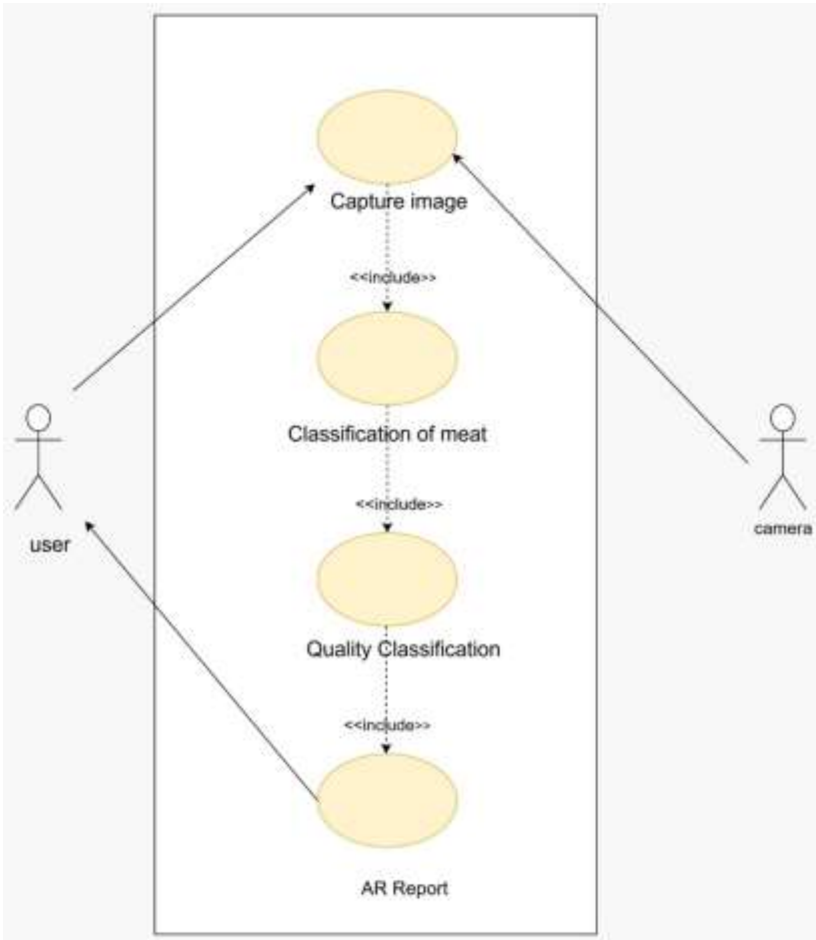

Figure 4.1: Use Case of the Project

4.4 USE CASE SPECIFICATION:

4.4.1 For User:

i. Capture images (for User)

UC-01: Capture Images	
Actors: User	
Features: This use case allows user to upload images to app	
Use Case Id:	UC-01
Pre-Condition:	The user must be logged into app
Scenarios: 1. Successful upload of image 2. Upload cancelled by user	
Exception Paths: Invalid file type or size exceeded	
Post Condition: File uploaded successfully	

Table 4.1: Capture images

ii. Classification of Meat Type(for User)

UC-02: Classification of Meat Type	
Actors: User	
Features: Automatically identifies the meat type (e.g., chicken, beef, or fish) from the captured image.	
Use Case Id:	UC-02
Pre-Condition:	Image must be successfully captured or uploaded.
Scenarios: 3. Correct classification of meat type 4. Unable to identify meat type	
Exception Paths: • Image too unclear or distorted • Invalid input format	
Post Condition: Meat type is classified and logged for quality analysis.	

Table 4.2: Classification of Meat Type

iii. Quality Classification (for user)

UC-02: Quality Classification of Meat Type	
Actors: User	
Features: Classifies the freshness of the meat as Fresh, Half-Fresh, or Spoiled based on deep learning model analysis.	
Use Case Id:	UC-03
Pre-Condition:	Meat type must be successfully identified.
Scenarios: 5. Accurate freshness label predicted 6. System returns “Uncertain” due to poor image quality	
Exception Paths: • Model failure • Timeout during inference	
Post Condition: Quality label is generated for the given meat sample.	

Table 4.3: Quality Classification

iv. Generate AR Report (for user)

UC-02: Quality Classification of Meat Type	
Actors: User	
Features: Displays the freshness classification label over the meat image using AR visualization.	
Use Case Id:	UC-04
Pre-Condition:	Freshness classification must be completed.
Scenarios: 7. AR label rendered successfully 8. AR overlay misaligned due to poor surface tracking	
Exception Paths: • AR module fails to load • Device doesn’t support AR	
Post Condition: AR report is generated and viewable in the app interface.	

Table 4.4: Generate AR report

Part V

Software Design Specification

(SDS)

This part covers the following topics:

- **Introduction**
- **Graphical User Interfaces**
- **Class Diagram**
- **Sequence Diagram**
- **Proposed Model**

5. Software Design Specification

This chapter presents the software design specification, explaining the purpose of the document. This whole chapter describes the graphical user interfaces (GUIs) for the main functionalities: image uploads, evaluation and recommendations, and report generation. The chapter includes class diagrams, sequence diagrams for image processing, meat evaluation, and report generation, and a proposed model with detailed descriptions.

5.1 Introduction

5.1.1 Purpose of Document

Software design specifications (SDS) are comprehensive document that outline the process by which a software system are developed to satisfy the requirements that are gathered at the beginning of a project. These specifications describe the system's architecture, parts, modules, interfaces, and data to meat predetermined standards. To ensure that all stake holders have a clear knowledge of how the software work, an SDS comprises models, descriptions, and diagrams that illustrate the structure and behavior of the system. It is essential for guaranteeing consistency, quality, and alignment with consumer needs and corporate objectives. It acts as a blueprint for developers, leading them through the implementation process.

5.2 GRAPHICAL USER INTERFACE

The proposed project has the following major interfaces.

5.2.1 User Interface Id: Image Upload Interface

Figure 5.1: Upload Images (Main Page)

Description

The Image Upload Interface is the initial step in the process of evaluating the structural condition of meat. This interface allows users, such as field technicians and users to capture and upload images and videos of meat directly from their mobile devices. The uploaded media is then sent to the server for further processing and analysis.

5.3 CLASS DIAGRAM

5.3.1 Class Diagram of the whole project

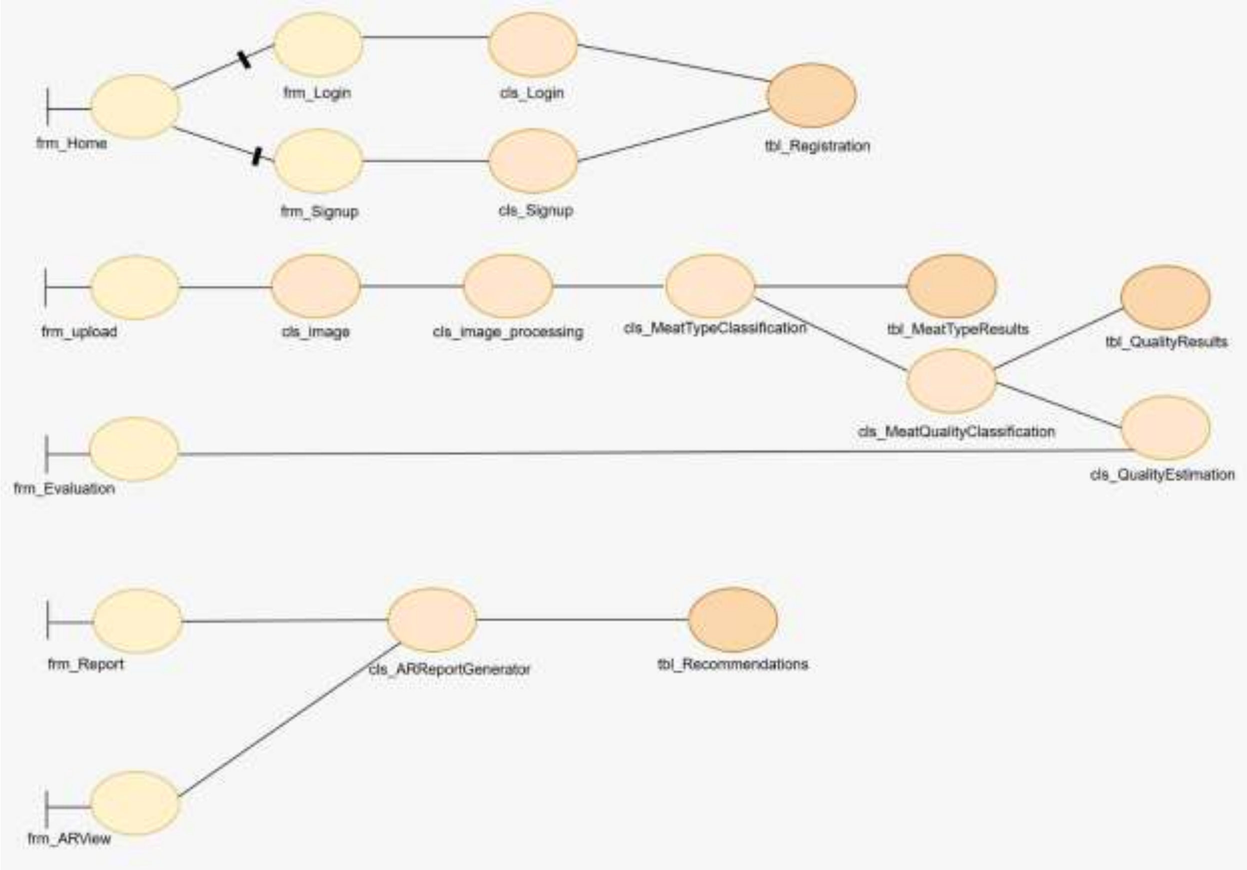

Figure 5.2: Class Diagram of the Project

5.3.2 Description:

Serial No.	Class Title	Description
1.	frm_Home	In this form, user login or signup.
2.	frm_Signup	In this form, user creates his/her account.

3.	frm_Login	In this form, user enter his id and password.
4.	frm_Upload	In this form, user upload meat image.
5.	frm_Evaluation	In this form, system displays meat evaluation.
6.	frm_Report	In this form, system shows quality report.
7.	frm_ARView	In this form, user views AR-based report.
8.	cls_Login	This class is used to login.
9.	cls_Signup	This class is used to signup.
10.	cls_Image	This class is used to capture meat image.
11.	cls_Image_Processing	This class is used to process meat image.
12.	cls_MeatTypeClassification	This class is used to classify meat type.
13.	cls_MeatQualityClassification	This class is used to classify meat quality.
14.	cls_QualityEstimation	This class is used to estimate quality.
15	cls_ARReportGenrator	This class is used to generate AR report.

16.	tbl_Registration	This table stores user registration data.
17	tbl_MeatTypeResults	This table stores meat type results.
18.	tbl_QualityResults	This table stores meat quality results.
19.	tbl_Recommendations	This table stores meat recommendations.

Table 5.1: Class Description

5.4 SEQUENCE DIAGRAM:

The Sequence diagram shows the internal connectivity of the object being used in the project. It is scenario-based and create three sequence diagrams of project. One scenario from each module and check its sequence diagram. The scenarios are

- Mobile Application Manager
- Image Processing
- Generate Report

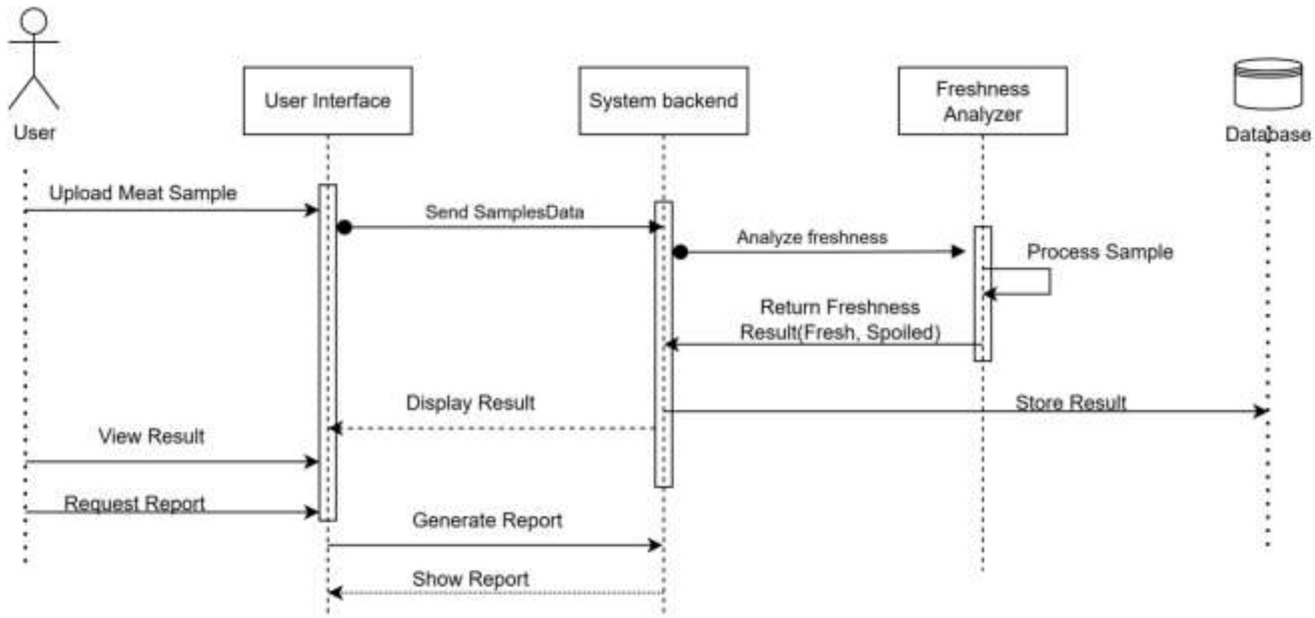

Figure 5.3: Sequence Diagram of the Proposed Project

5.4.1 Mobile Application Manager

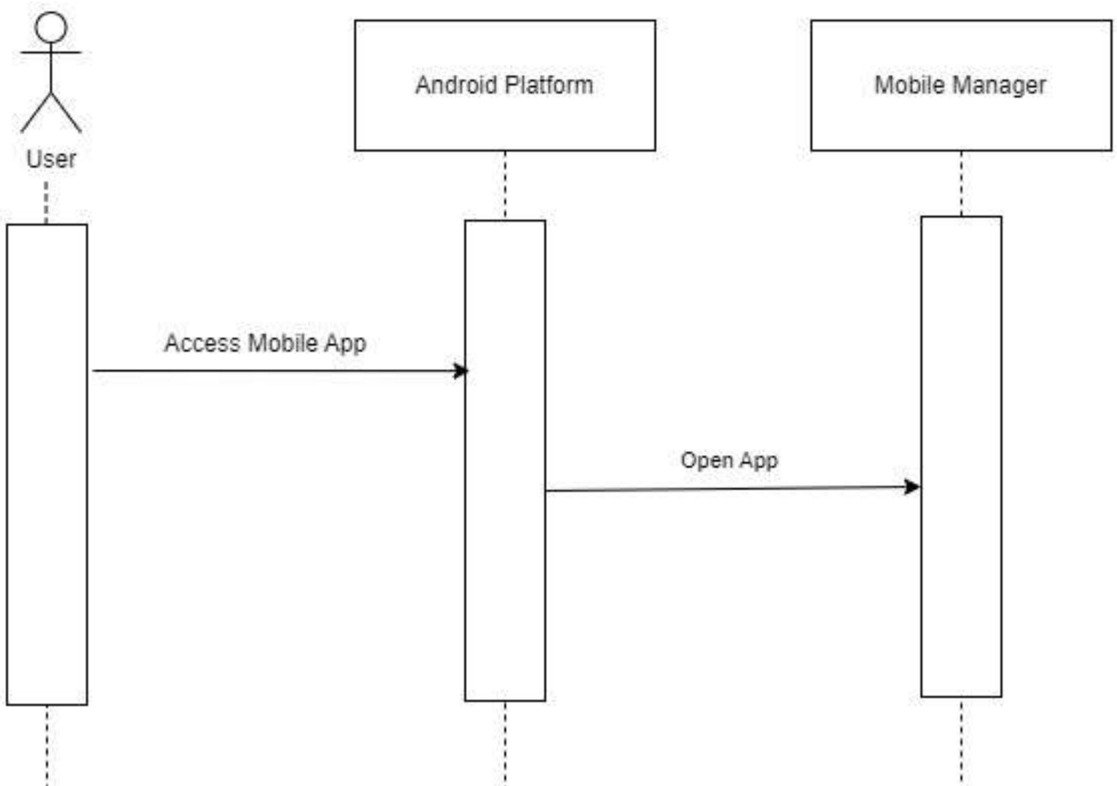

Figure 5.4: Scenario of Mobile Application Manager

Description:

This sequence diagram shows a user accessing the Meat Quality App via the Android platform on a smartphone.

5.5 PROPOSED MODEL:

5.5.1 Diagram

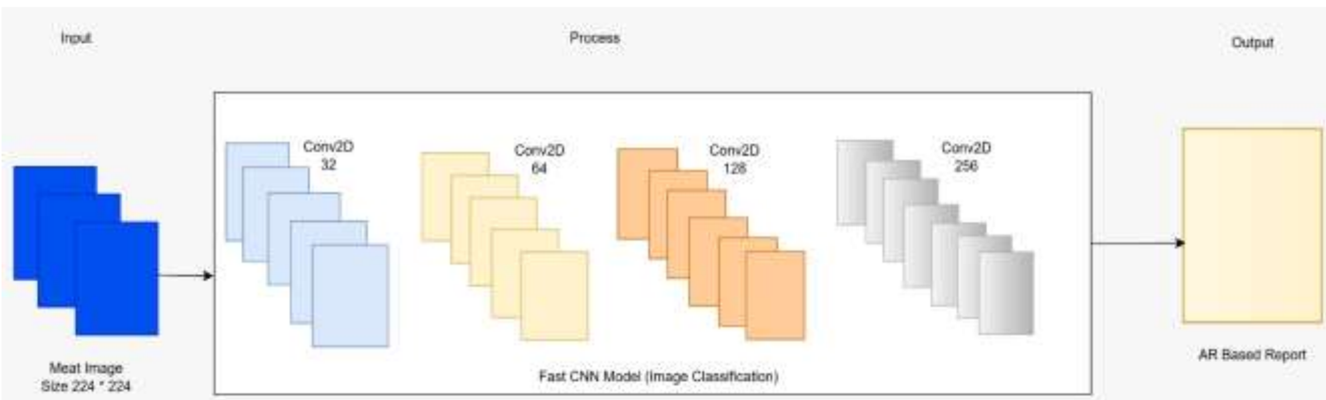

Figure 5.10: Proposed Model Diagram

5.5.2 Description:

The proposed model employs a multi-stage approach using Convolutional Neural Networks (CNNs) to evaluate the structural behavior of images. Initially, images captured are processed by the first CNN model, the extracted features are then passed to a second CNN model that classifies the meat as fresh, slightly spoiled and spoiled. Based on the classification results, the proposed project provides recommendations such as whether the meat is safe to consume or needs refrigeration.

Part VI

Software Test Specification

(STS)

This part covers the following topics:

- **Introduction**
- **Scope of Testing**
- **Test Plan Strategy**
- **Control Procedures**
- **Test Cases**

6. Software Test Specification

This chapter presents the software test specification, stating the document's purpose and the scope of testing. The test plan strategy, covering unit testing, integration testing, and system testing is described. Control procedures, such as reviews, bug review meetings, and change requests, are also discussed. Detailed test cases for key functionalities, including image acquisition via mobile camera, raw meat type classification, meat quality evaluation, quality assurance estimation using AI techniques, and AR-based report generation is provided.

6.1 Introduction

6.1.1 Purpose of Document

The purpose of the test plan is to achieve the following

- Define the activities required to conduct unit, integration, and system testing.
- Communicate to all team members the various dependencies and risks.

6.2 Scope Of Testing

The proposed project i.e. Raw Meat Quality Assurance performs the unit, integration, and system testing approach. At the end of each increment, the testing is done. The testing phase includes:

1. End-to-end testing of all interfaces of the Raw Meat Quality Assurance.
2. Testing all sequence diagram scenarios discussed in the software design specification.
3. Testing Project code.
4. Review the module's results.
5. Audit the developed module's results.
6. System and Acceptance Testing.

6.3 TEST PLAN STRATEGY

The test plan strategy consists of a series of different tests that are fully exercised in "Raw Meat Quality Assurance". The primary objective of these tests is to ensure that the project meet the full requirements, including quality requirements also satisfy the use case scenarios, and maintain the quality of the product. The secondary objective of these tests is to uncover the limitations of the proposed and measure its full capabilities. Testing approaches that are used include white box and black box testing.

A list of the planned tests and their brief explanation given below

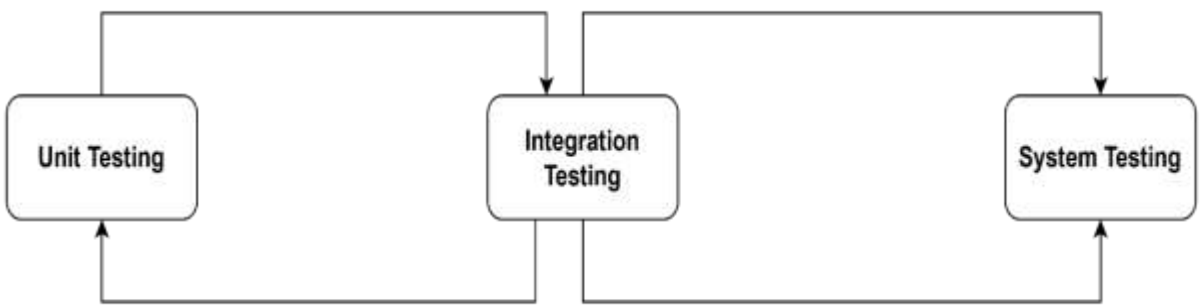

Figure 6.1: Testing Diagram of proposed project

6.3.1 Unit Testing

Unit testing is conducted after each increment to ensure that proper functionality has been achieved.

The following are the example areas of the project that must be unit-tested before being passed into integration testing which monitors

- The user profile handling functionalities for both consumers and food authorities.
- The image acquisition module for capturing raw meat images through the mobile device.

- The image processing module for refining and preparing images using computer vision techniques (i.e, Fast CNN, RestNet).
- The classification modules for raw meat type and quality based on deep learning models.
- The quality assurance estimation module, which uses AI techniques (e.g., fuzzy logic) to provide confidence levels for meat quality.
- The augmented reality (AR) based report generation module provide meat type classification and information about meat quality.

6.3.2 Integration Testing

Integration testing is a logical extension of unit testing. After unit testing, all increments are merged and the application is tested.

6.3.3 System Testing

After integration testing, convert the software into packages and then test the system to check overall system success.

6.4 CONTROL PROCEDURES

6.4.1 Reviews

The project team will perform reviews for each phase (i.e. requirements review, design review, code review, test case review and final test summary review). All the team members will be notified about the meeting a day before.

6.4.2 Bug Review Meetings

Regular meetings will be held to discuss listed defects.

6.4.3 Change Request

If any change is required the team members will analyze the change and then implement it according to the plan given in PMP.

6.5 TEST CASES

6.5.1 Test Case1: "Upload Image"

Test Case ID	**TC_RMQA_001**	**Tester: Ayesha Munawar**
Application Name	**Raw Meat Quality Assurance**	**Date: 22nd June 2025**
Purpose	To verify that user can successfully upload images to the app	
Scenario	User attempts to upload image files to app, including valid uploads and handling of invalid file types.	
Environment	Android	
Pre-Request	→User must have access to the upload feature. →System should have defined size and limits for upload. →RMQA Server in ON. →Server's Application is running.	
Strategy	1. Validate successful uploads of images 2. Ensure the system handles errors such as invalid file types	
Expected Results	Display a message that images successfully uploaded to the app	
Observations	1. Check system response time during upload. 2. Verify error messages are clear and informative. 3. Monitor system behavior with multiple concurrent uploads (if applicable).	
Result	Display message that images executed successfully.	

6.5.2 Test Case2: "Classify Raw Meat Type"

Test Case ID	**TC_RMQA_002**	**Tester: Raeesa Asif**
Application Name	**Raw Meat Quality Assurance**	**Date: 2nd July 2025**
Purpose	To verify the system can correctly classify uploaded images into raw meat categories: poultry, livestock, or seafood.	
Scenario	After uploading, the system should classify the image into one of the supported raw meat types using a trained deep learning model.	
Environment	Android	
Pre-Request	→A valid raw meat image must already be uploaded. → The classification model must be trained and deployed on the server.	
Strategy	1. Validate accurate classification of meat type. 2. Confirm fallback handling for unrecognized images.	
Expected Results	The system correctly identifies and labels the raw meat as poultry, livestock, or seafood.	
Observations	4. Measure classification time. 5. Review system accuracy across multiple image types. 6. Confirm proper logging of classification results.	
Result	Meat type displayed successfully based on system classification.	

6.5.3 Test Case3: "Classify Raw Meat Quality"

Test Case ID	**TC_RMQA_003**	**Tester: Shifa Zahra**
Application Name	**Raw Meat Quality Assurance**	**Date: 12th June 2025**

Purpose	To verify that the system can accurately classify the quality of raw meat images using defined metrics and models.
Scenario	User uploads an image, and the system classifies the quality into defined categories (e.g., Fresh, Half-Fresh, Spoiled).
Environment	Android
Pre-Request	→Valid image must be uploaded and classified for type. →Quality classification model must be deployed and active.
Strategy	1. Validate correct quality classification based on trained dataset. 2. Test classification on different quality levels.
Expected Results	Quality classification result is displayed (e.g., Fresh) with accuracy aligned with predefined quality metrics.
Observations	7. Assess classification precision. 8. Monitor system under varied lighting/image conditions. 9. Review how borderline cases are handled.
Result	Raw meat image classified into the correct quality category.

6.5.4 Test Case4: “Generate AR-Based Quality Report”

Test Case ID	**TC_RMQA_004**	**Tester: Ghania Shahzad**
Application Name	**Raw Meat Quality Assurance**	**Date: 22nd July 2025**
Purpose	To verify that the AR module correctly generates and displays a visual quality report for the uploaded meat item.	

Scenario	User views an AR report overlay showing meat type, quality, and estimation in real time.
Environment	Android
Pre-Request	→All prior steps (upload, classification, estimation) must be completed. →AR module and camera permissions must be enabled.
Strategy	1. Validate real-time rendering of AR report. 2. Confirm correct overlay of classification and estimation data.
Expected Results	AR report is generated showing the meat's type classification and quality estimation.
Observations	10. Evaluate AR alignment and responsiveness. 11. Test on different surfaces and lighting conditions. 12. Review user feedback on clarity of AR display.
Result	AR-based report displayed successfully.

Part VII

Limitations, Conclusion, and Future Enhancement

This part covers the following topics:

- **Limitations**
- **Conclusion**
- **Future Enhancements**

7. Limitations, Conclusion, and Future Enhancement

This chapter presents the project, highlighting the key outcomes and achievements. The reflection on the overall impact and effectiveness of the proposed project. Additionally, discussing the potential future enhancements, suggesting areas for improvement and further development to enhance the project's functionality and user experience.

7.1 Limitations

The project's reliance on mobile camera technology means it can be affected by environmental factors such as lighting conditions, background noise, and camera quality, which may limit its effectiveness in certain usage scenarios. Additionally, high-resolution image capture and processing require substantial device resources, potentially hindering performance on less capable Android devices. The accuracy of the computer vision and deep learning models is dependent on the quality and diversity of the training dataset, which, if insufficient, can result in misclassification or inaccurate quality estimation. Packaged or frozen raw meat poses challenges for the system, as reflections, condensation, and wrapping material can interfere with visual analysis, making such products unsuitable for evaluation. Real-time functionality may also impacted in areas with poor network connectivity, especially where server communication or cloud processing is involved. Regular maintenance, model re-training, and updates are necessary to sustain system accuracy and performance, requiring ongoing development effort. Finally, the application handles potentially sensitive consumer or vendor data, making data protection and cyber security critical to ensuring trust and compliance.

7.1 CONCLUSION

The project represents a significant technological advancement in food quality assurance. By integrating computer vision, deep learning, and augmented reality, it offers an efficient, accurate, and user-friendly solution for raw meat quality assessment. Automated image-based evaluation reduces dependency on costly and time-consuming laboratory methods, while AI-driven classification ensures precise analysis of meat type and quality. The project enhances consumer and regulatory confidence by enabling real-time, non-destructive inspection directly from mobile devices. Comprehensive testing has validated its performance, usability, and accuracy, making it a practical tool for both everyday consumers and food authorities. The proposed project sets a new standard for leveraging intelligent technology in food safety and quality monitoring.

7.2 Future Enhancements

Future enhancements for the raw meat quality assurance mobile application will include improved deep learning models to enhance classification accuracy across a wider variety of meat types and conditions. Augmented Reality (AR) features will be further enriched to deliver more interactive and intuitive quality reports. Integration with national food authority databases and traceability systems will support regulatory compliance and validation. A cloud-based infrastructure will provide scalable storage for large image datasets and enable remote access for food inspectors and vendors. Real-time quality feedback will be optimized for speed and accuracy through edge computing. The user interface will be redesigned to improve accessibility for low-literacy users. Support for additional languages and regional settings will expand usability. Packaging detection algorithms will be introduced to alert users when meat is wrapped or frozen and not suitable for accurate scanning. Finally, periodic model retraining will be implemented to maintain performance as new data becomes available, ensuring continued reliability and relevance.

Annexure “A”

This part covers the following topics:

- **Literature Review**
- **Software Based Review**

A.1 Literature Based Solutions:

Table 1: Review of Literature for Meat Quality Assurance

Author /Year	Proposed idea domain	Proposed solution	Types of raw meat items	Microorganisms Indicators	Quality features	Sampling approach	Proposed methodology	Proposed technique	Proposed tool	Hardware capture	Dataset			Testing Environment
											Type	**No of instances**	**Acquisition source**	
Xiao Hong Wu , 2024 [1]	Food science	Integrated system that employs various non-destructive detection techniques	Beef , Poultry Lamb, Mutton pork	Physiological Morphological, sensory	Color, tenderness, texture, pH levels, fat content, protein, smell, taste	Non destructive	Machine Learning , AL	Spectroscopic , Imaging Techniques Machine vision, electronic nose	Spectrometers (NIR, Raman Infrared cameras , gas sensors	Spectrometer, digital camera	Thermal images	100	Customized data set	Real time
Philip Donald C. Sanchez,2022 [2]	Food science	Quantification and Visualization of Meat Quality	Pork, Beef	Physiological, Morphological	Color, tenderness, texture, pH levels ,fat content, Biogenic Amine Content, Oxidation (Lipid and Protein) protein	Non destructive	Machine Learning, Deep Learning	Hyperspectral Imaging (HSI), Spectral Data Acquisition	hyperspectral camera	Camera, Spectrograph, Illumination units	Hyperspectral images.	150	Customized	Laboratory
Kyung Jo, 2024 [3]	Food science	Assessment report	Beef, Pork, Poultry	Physiological Morphological	**Appearance, size, tenderness color , marbling** pH levels, water-holding capacity, and oxidation	Non-destructive	Machine Learning	Hyperspectral Imaging	HSI spectrometer	Camera	3D Hyperspectral Image	200	**Public repositories**	Real time
Valeriy Zaytsev , 2024 [4]	Food sciences	**e-nose** based on **semiconductor metal oxide gas sensors**, **RGB computer vision**	**Beef, pork, poultry, lamb**.	**Brochothrix**, **Pseudomonas**, **Acinetobacter**, **Flavobacterium**,	**Spoilage-related gases**, **Color changes**	Non-destructive	Machine Learning	**Volatile compound analysis**, **RGB imaging**	**e-nose**, **computer Vision (RGB)**, **mass spectrometry**, machine learning	**Sensor RGB cameras**	Multi sensor data	335	**Online**	Laboratory

Linyu Zhang ,2023 [5]	Food Bioscience	Intelligent detection technologies	Beef, Pork, Chicken, Fish, Lamb	Physiological, Morphological	Color, texture , odor , pH level ,water activity , fat content	Non-destructive	Artificial Intelligence, Machine Learning	Spectroscopic, Electromagnetic, Biosensors	Spectrometer, Smart biosensors	NIR Spectrometer, Hyper spectral cameras, biosensors	Spectral images	Not mentioned	Customized	Real-time
Eric Zhou, 2024 [7]	Meat science	Fluorescence-based prototype device	Beef	Physiological , Morphological	Color, marbling,pH level, Collagen Content, Oxidative State of Myoglobin	Non destructive	Machine Learning	Auto fluorescence imaging	Prototype device using 3D nm LED and CMOS camera	CMOS Camera	Spectral image	200-300	Beef samples from a meat supplier	Laboratory
Marcin Wegner,2024 [8]	Agricultural science	Guidline	guinea fowl	Physicochemical, physiological	Protein fat content, Collagen, salt content, pH, Tenderness, Springiness, Gumminess, hardness,	Destructive	NIR, Electrical Conductivity, Colorimetry, Texture Profile Analysis, Warner - Bratzler Shear Force Test	NIR Analyzer, Electrical Conductivity Probe	Near-Infrared Spectroscopy (NIR)	Food Scan Analyzer, CX-701 pH Meter, LF-Star CPU Probe, TA.XT Plus Texture Analyze , Electric Meat Grinde	Meat sample	10 male guinea fowl 10 female guinea fowl	Customized	Laboratory
Bukola M. Adenuga, 2025 [9]	Food Industry	Use of DNA-based methods (PCR)	Red deer meat	Physiological	High nutritional value, low fat, high protein, low heavy metals	Non destructive	Deep learning	Real-time PCR	SYBR Green PCR assay for species-specific identification	PCR instruments, DNA extraction, amplification tools	**Review Articles**, Published Research Papers	Multiple samples from 3 countries (Poland, Portugal, Spain)	Online	Laboratory
Stefaan De Smet ,2024	Public Health and Meat Safety	Evaluation of sustainable meat production	Beef, Pork, Poultry	Physiological	High protein, vitamins	Non destructive	Machine learning	Environmental modeling	Food analysis software	Spectrophotometer, Environmental	Online database	200	National health surveys	Laboratory

[10]										monitoring devices				
Zhe Sha, Weiqing Lan 2024 [11]	Food science and technology	Development of Colorimetric freshness indicators (CFIs)	seafood(fish, shellfish)	Morphological, physiological	pH, color freshness, spoilage , color ,odour	Non destructive	Deep Learning	Colorimetric technique	Colorimetric freshness indicators (CFIs)	Sensors, spectrophotometer	Images	Above 400	Experiments in labs	Laboratory
Poonguzhali Elangovan, 2024 [12]	Food Safety	Automated system that utilizes shallow (CNNs) to assess the quality	Beef, Poultry, Pork, Fish	Physiological	Color, texture , odor , tenderness	Non-destructive	CNN model	ConvNet-18 and ConvNet-24 CNN models, Ensemble models	Imaging devices , CNN framework	Cameras, AI processors, Spectrometers	Image data, Spectral data	Variable	Meat processing facilities, abattoirs, retail distribution centers	Real time
Benjamin W.B. Holman ,2021 [13]	Food science	Guidelines for Meat Quality Assessment	Beef , Sheep	Physiological	Tenderness, color, juiciness, flavor,	Destructive	Laboratory assessments with sensory evaluations	Colorimeter, Texture analyzer,	-	pH Meter, Hedonic Scales, Drying Apparatus	Raw meat sample	200	Customized	Laboratory
Dwi Agustina Kurniawati, 2024 [14]	Halal supply chain optimization	Automated spoilage detection model	Chicken, Beef, Pork	physiological	Freshness, Tenderness, pH, Color	Non-destructive	Deep learning AI, CNN	Convolutional Neural Networks	Imaging Devices	Sensors, Cameras	Image Dataset	5,000+ Images	Halal food logistics	Laboratory
Viorica Bulgaru, 2022 [15]	Food science	Evaluating the aging process	Beef (dry-aged)	Physiological	Tenderness, juiciness, flavor, color, moisture content	Destructive	Physicochemical tests (moisture, fat conten) , sensory tests	Moisture content, texture analysis	Texture Analyzer, Colorimeter, pH meter	Incubators for aging room	Structured dataset	Multiple samples at stages (e.g., 3, 7, 14, 28 days)	Customized	Laboratory
Kudzai N. N gong	Food Processing	Acacia mearnsii bark extracts	Beef patties	Reactive oxygen species	Oxidative deterioration, shelf-life	Destructive	Literature review, case studies	DPPH, TBARS assays	Analytical tools	Quantitative data	images	20 instances	Lab extracted	Laboratory

oni, 2025 [16]														
Zhe Shao, 2024 [17]	Food science	Application of CFIs to detect freshness and spoilage	Aquatic products	Spoilage bacteria	Freshness, spoilage indicators	Non destructive	Machine learning	Colorimetric freshness indicator (CFI) deployment	Green extraction tools	Experimental samples	Experimental data	100+ samples	Samples sourced from storage experiments	laboratory
Yuan daong,2024 [17]	Food industry	Real-time quality monitoring	Chilled beef	Physiological	Fresh , slightly spoiled	Non - destructive	Deep Learning, Machine Learning	CSA, camera , scanner, Colorimetric sensor array, camera, scanner	CNN, t-SNE, HCA, PCA	Camera, sensors	Images	400+	Online	Real time
BirkanBuyukarikan,2024 [18]	Food Safety , healthcare	To classify beef quality , reduce waste and improve f ood safety	Fresh half, Fresh spoiled	Physiological	Color, texture, PH level , Marbling , Fat color, odur	Non destructive	Deep learning, frameworks	DNN (Deep Neural Network, CNN, LSTM, Bi-LSTM (Bidirectional LSTM)	Digital cameras	Google Cloud Platform Digital cameras	Images	2266 RGB images of beef	Experiments available in lab	Real time
Gong shuai, 2024 [19]	Food science, analytical technology	Rapid Evaporative Ionization Mass Spectrometry (REIMS), Support Vector Machines (SVM) , Gradient Boosting Machines (GBM)	Beef	Physiological, morphological	pH, Moisture Content, Texture , color, Cut Type ,chemical composition	Non destructive	Machine learning , Data Science , Mass Spectrometry (MS) , Cloud Computing	Imaging, Machine Vision	REIMS Device (Rapid Evaporative Ionization Mass Spectrometry)	Mass Spectrometer, Digital cameras , Mobile or Handheld Devices (for portable testing	Images	100	Develop a system that accurately identifies and distinguishes b/w correctly and incorrectly labeled beef cuts	Real time

N. Berdusco,2024 [20]	Food science	Integrating AR for sensory evaluation, safety inspections, traceability	Food items	**Sensor, physiological**	Sensory quality, freshness, safety	Systematic literature review, industry data collection	Systematic review and analysis of AR technology in food	food quality analysis	AR devices, sensors, mobile AR applications	AR sensors, 3D cameras	Literature review, **Review Articles**	50+	Public academic databases, industry reports	laboratory

A.2 Software Based Solutions:

Table 2: Review of software-based solutions for Raw Meat Quality Assurance

Tool	**Cost**	**Features**	**Device**
Raman Spectroscope [1]	Paid	Chemical Composition, Moisture Content, Foreign Object Detection:	Hyperspectral Imaging (HSI) Systems, X-ray Imaging Systems
Strenuous [7]	Paid	Color, marbling ,pH level, Collagen Content, Oxidative State of Myoglobin	CMOS Camera
Hyperspectral Imaging (HSI), Magnetic Resonance Imaging (MRI), Raman Spectroscopy [2]	Paid	Color, tenderness, texture, pH levels ,fat content, Biogenic Amine Content, Oxidation (Lipid and Protein) protein	Hyperspectral Imaging (HSI), Spectral Data Acquisition
Raman Spectroscopy [3]	Paid	**Appearance, size, tenderness color, marbling** pH levels, water-holding capacity, oxidation	Camera, 3D Hyper spectral Image
Sensor RGB [4]	Unpaid	**Spoilage-related gases**, **Color changes**	**e-nose** based on **semiconductor metal oxide gas sensors**, **RGB, computer vision**
Chemical Composition Analysis, Physicochemical Properties Analysis, Texture Analysis [8]	Unpaid	Protein fat content, Collagen, salt content, pH, Tenderness, Springiness, Gumminess, hardness	Near-Infrared Spectroscopy (NIR)

PCR instruments, DNA extraction, amplification tools [9]	Unpaid	High nutritional value, low fat, high protein, low heavy metals	PCR assay for species-specific identification
Microbial Supplements, Lipidomics and Proteomics, Molecular Biology, Statistical and Computational [10]	Paid	Intramuscular Fat Content, Muscle Fiber Type, Flavor Compounds, Amino Acid Profiles:	Camera
Colorimetric technique [11]	Paid	pH, color freshness, spoilage, color, odor	Colorimetric freshness indicators (CFIs)
Bionic Technology, Spectral Technology, Electromagnetic Characteristic Technology, [5]	Unpaid	Convenience and Speed, Low Cost,	Spectrometers, Electronic Nose (E-nose), Electronic Tongue (E-tongue)
Imaging Technology, Artificial Intelligence (AI) Technology [12]	Paid	Automated Processing, Rapid and Accurate Detection	Sensors, Processors
Consumer and Trained Sensory Panels, Laboratory-Based Methods [13]	Paid	Predefined Sensorial Properties, Threshold Definition	Texture Analyzers, Scoring Instruments for Sensory Panels
Big Data Analytics, Mixed Integer Linear Programming (MILP) Model [14]	Unpaid	Halal Integrity and Cross-Contamination Prevention, Operational Cost Considerations, Shelf Life and Delivery Window	IOT Devices, AI-Based Decision Tools, Cloud Computing Platforms
Wet and Dry Aging Techniques, Calpain and Cathepsin Enzymes, Controlled	Unpaid	Tenderness, Juiciness and Aroma, Chemical Composition Analysis, Enzymatic Activity, Sensory and Texture Indices	Refrigerated Aging Rooms, Physicochemical Testing Equipment

Environment Parameters [15]			

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