IDENTIFICATION OF CHEMICALS IN FISH USING MACHINE LEARNING AND IOT

a project report submitted by

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BONAFIDE CERTIFICATE

Certified that this project report **"IDENTIFICATION OF CHEMICALS IN FISH USING MACHINE LEARNING AND IOT"** is the bonafide work of "Y. SRI GANESH REDDY (REG. NO: URK20CS1043)**"** who carried out the project work under my supervision.

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Submitted for the Project Viva Voce held on……………………….

Examiner

Abstract

Ensuring the freshness of fish is not only vital for maintaining food safety but also crucial for preserving its nutritional value, as fish is a cornerstone of many diets worldwide. Apart from visual cues like clear and bright eyes indicating freshness, other factors such as firm flesh and a mild odour also contribute to assessing the fish's quality. With fish often traversing long distances before reaching consumers, effective chilling methods during transportation play a pivotal role in preserving its freshness and preventing spoilage.

However, the use of chemical preservatives like formaldehyde raises concerns about the potential health risks associated with consuming treated fish. In response, our research aims to develop reliable methods for detecting formaldehyde residues on fish surfaces. By utilizing advanced detection technologies capable of identifying volatile organic compounds, we can accurately assess the extent of formaldehyde treatment without compromising on efficiency.

Furthermore, our approach incorporates a strategic testing protocol that prioritizes fish based on initial visual assessments of freshness. This ensures that resources are allocated efficiently, focusing on verifying the quality of fish that pass the preliminary inspection. Ultimately, our efforts seek to empower consumers by providing them with transparent information about the fish they consume, thereby promoting safer and higher-quality seafood choices.

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SL. No	Abbreviation	Definitions
1.	AI	Artificial Intelligence
2.	ML	Machine learning
3.	SVM	Support Vector Machine
4.	UI	User Interface
5.	TP	True Positive
6.	TN	True Negative
7.	LCD	Liquid Crystal Display
8.	HTML	Hyper Text Morkup Language
9.	CSS	Cascading Style Sheets
10.	IoT	Internet of Things

CHAPTER I

INTRODUCTION

The global demand for fresh fish continues to surge as it remains a vital source of nutrition for populations worldwide. However, guaranteeing the freshness and quality of fish products is becoming increasingly challenging, particularly in regions where fish consumption is prevalent. Various factors contribute to the deterioration of fish quality post-harvest, including lipid oxidation, enzymatic degradation, and bacterial decay, underscoring the urgent need for efficient techniques to assess and preserve seafood freshness along the supply chain.

In recent years, there has been a surge in research aimed at developing innovative methods for evaluating fish freshness. These methods span from traditional sensory analysis to more sophisticated technologies, including image processing, machine learning, and Internet of Things (IoT)-based sensing. Visual cues, such as the condition of fish eyes and gills, have been explored for real-time freshness assessment, while machine learning algorithms like VGG-16 and MobileNetV1 have shown promising results in automating freshness classification tasks with remarkable accuracy.

This study presents a novel approach to fish freshness identification by harnessing machine learning algorithms, specifically MobileNetV3 and Inception Net, to analyze fish eye images. By leveraging the capabilities of these state-of-the-art algorithms, our aim is to not only enhance the accuracy and efficiency of freshness classification but also contribute to the advancement of food safety regulations within the fishing industry. Moreover, our research seeks to deepen the understanding and utilization of machine learning techniques to ensure the freshness and quality of fish products, thus benefiting consumers and stakeholders across the supply chain.

Furthermore, the significance of fish as a crucial nutritional resource cannot be overstated, especially considering the projected global population increase and rising food consumption rates. With over half of the world's aquatic food sourced from the ocean, ensuring the freshness and safety of fish products becomes imperative. Therefore, this research not only addresses the immediate need for effective freshness assessment but also contributes to long-term efforts aimed at sustainably meeting the nutritional demands of a growing population.

Moreover In Fig -1.1 shows their noteworthy to highlight some numerical data regarding fish consumption and production. In 2018, the global per capita fish consumption stood at 20.5 kg, marking a significant increase from 9.0 kg in 1961. Additionally, the average annual global consumption of fish and fish products reached 18.4 kg per person, with a total worldwide consumption of 128 million tonnes. Indonesia, being the second-largest fish producer after China, plays a crucial role in the global seafood market, contributing substantially to the economy and providing essential animal protein to its population.

Overall, this study aims to provide a comprehensive examination of the methodologies and techniques utilized in the identification and detection of chemical compounds and freshness in edible fish. By integrating machine learning and IoT technologies, we aspire to revolutionize the approach to fish freshness assessment and ensure the continued availability of safe and high-quality seafood for consumers worldwide.

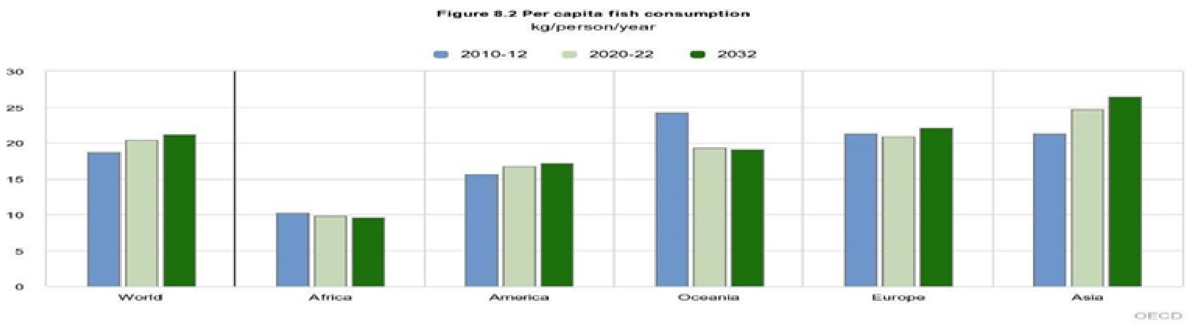


Fig -1.1 Shows the Per capita Fish Consumption in Recent Years

1.1 Objective of Research

This research project aims to develop a comprehensive system that can effectively determine the freshness of fish and detect the presence of formaldehyde preservatives, using a combination of image processing, machine learning, and IoT technologies. By analysing visual indicators such as the appearance of the fish's eyes, the system can assess its freshness, while a specialized formaldehyde detector identifies any harmful preservatives. This integrated approach is designed to provide consumers with real-time information about the quality of the fish they are considering purchasing, potentially through a user-friendly web application. Through thorough testing and refinement, the goal is to improve food safety practices, increase consumer awareness, and advance technological solutions for ensuring the quality of fish products in the market

1.2 Problem Statement

The research seeks to tackle the challenge of efficiently and accurately assessing the freshness and safety of fish products in the market. Traditional methods for evaluating fish freshness are often costly, time-consuming, and require specialized skills. Additionally, concerns have emerged regarding the potential presence of harmful chemical preservatives like formaldehyde in fish intended for consumption. Therefore, there is a critical need for a solution that can swiftly detect fish freshness and identify any harmful chemical additives, enabling consumers to make informed decisions about the fish they buy and consume, thereby ensuring both quality and safety.

1.3 Chapter wise summary

Chapter 1: Introduction

Introduces the importance of assessing fish freshness and safety in the context of global consumption trends and the potential risks associated with chemical preservatives.

Chapter 2: System Analysis

Analyzes existing methods for evaluating fish freshness and identifies the shortcomings that necessitate the development of an automated detection system.

Chapter 3: System Design

Details the design considerations and requirements for implementing a system capable of detecting both fish freshness and the presence of harmful chemical additives.

Chapter 4: Implementation

Describes the technical implementation of the proposed system, including the integration of sensors, machine learning algorithms, and IoT devices.

Chapter 5: Results and Discussion

Presents the findings of the system's performance evaluation, discussing the accuracy and effectiveness of freshness detection and chemical analysis.

Chapter 6: Conclusion and Future Scope

Summarizes the project outcomes, highlights the significance of the developed system, and outlines potential avenues for future research and enhancements.

CHAPTER 2

SYSTEM ANALYSIS

2.1 Existing System

Fish freshness classification was attempted by Iswari et al. (2007) using fish images and the k-Nearest Neighbor algorithm, indicating a viable approach for assessing fish quality based on visual characteristics (1).

Abu Rayan et al. (2019) developed a robust fish freshness classification system by combining deep learning models, showcasing significant improvements in accuracy and reliability compared to conventional methods (2).

Sengar et al. (2018) introduced an image processing-based technique for identifying fish freshness through skin tissue analysis, offering a non-invasive method for assessing fish quality (3).

Jarmin et al. (2018) conducted a comprehensive comparison of fish freshness determination methods, shedding light on the strengths and weaknesses of various approaches in this domain (4).

Gu et al. (2023) proposed a novel detection method for fish freshness leveraging advanced sensor technologies, promising enhanced accuracy and efficiency in freshness assessment (5).

Kumar et al. (2020) developed an intelligent system utilizing artificial neural networks for fish freshness quality assessment, demonstrating the potential of machine learning in ensuring food safety (6).

Zhang et al. (2022) provided an overview of emerging approaches for fish freshness evaluation, addressing key principles, applications, and challenges in this rapidly evolving field (7).

Guo et al. (2022) introduced a fish freshness evaluation method based on MobileNetV1 and attention mechanism, offering a robust and efficient solution for real-time freshness assessment (8).

Arora et al. (2023) proposed an image processing-based automatic identification system for freshness in fish gill tissues, contributing to the development of automated freshness assessment technologies (9).

Sooai (Year) presented a model for analyzing the freshness of DECAPTERUS MACARELLUS fish, providing insights into factors influencing fish freshness and quality (10).

R et al. (2023) developed an IoT and machine learning-based system for identification and detection of freshness in edible fishes, showcasing the potential of advanced technologies in ensuring food safety (11).

Kılıçarslan et al. (2024) conducted a comprehensive study on fish freshness detection through artificial intelligence approaches, delving into the intricacies of utilizing AI for assessing the freshness of fish products. Their research encompassed a wide array of AI techniques, including machine learning algorithms and computer vision methods, to accurately evaluate the quality of seafood. By exploring the latest advancements in AI technology and their applications in the food industry, the study provided valuable insights into the challenges and opportunities associated with implementing freshness assessment technologies. Furthermore, Kılıçarslan and colleagues outlined potential future directions for research and development in this field, highlighting the importance of continued innovation to meet evolving food safety standards and consumer demands (12).

Abu Rayan et al. (2021) proposed a fish freshness classification system using a combined deep learning model, showcasing the efficacy of advanced machine learning techniques in safeguarding food quality and safety. Their research focused on leveraging deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to classify fish based on freshness indicators extracted from sensory data. By employing a combination of sensor fusion techniques and sophisticated machine learning models, the proposed system demonstrated remarkable accuracy in classifying fish products according to their freshness levels. Abu Rayan and his team emphasized the potential impact of their work on enhancing food quality control processes in the seafood industry, paving the way for automated freshness assessment systems that ensure compliance with regulatory standards and consumer expectations (13).

In their study, researchers developed an IoT and machine learning-based system for the identification and detection of freshness in edible fishes. By integrating sensor data with advanced algorithms, the system could accurately assess the quality of fish products in real-time, offering significant improvements in food safety and quality assurance protocols (14).

Kılıçarslan et al. (2024) conducted an extensive study on fish freshness detection through artificial intelligence approaches, providing valuable insights into the current landscape and future directions of freshness assessment technologies in the food industry. Their research shed light on the challenges and opportunities associated with implementing machine learning techniques for ensuring the freshness and quality of seafood products, emphasizing the need for continued research and innovation in this domain (15).

2.2 Proposed System

The proposed system integrates image processing and machine learning techniques to assess fish freshness and detect formaldehyde presence, ensuring food safety. Utilizing a webcam, real-time fish images are captured for freshness identification by analysing iris texture, employing MobileNetV3 and Inception-Net algorithms for classification.

A formaldehyde sensor interfaced with an Arduino Uno microcontroller detects formaldehyde levels, triggering warnings if concentrations exceed safety thresholds. Data preprocessing enhances image quality, while a dataset sourced from an internet repository facilitates algorithm training. The system's hardware setup includes an HCHO gas sensor linked to an Arduino Uno board, with data transmission facilitated via a Wi-Fi module to a cloud storage and Blynk app interface. This integrated approach enables real-time assessment of fish quality and chemical contamination, enhancing consumer safety and confidence in seafood products.

2.2.1 Algorithms Architecture

Mobile net Version 3 and Inception net: MobileNetV3 is a state-of-the-art convolutional neural network architecture created especially for successful mobile and embedded vision applications. It builds upon previous Mobile Net versions with novel features such as depth-wise separable convolutions, linear bottlenecks, and efficient inverted residuals to accomplish a trade-off between model size, performance, and accuracy.

In Fig-2.1 , Introduced by MobileNetV3 are squeeze-and-excitation modules for improved feature representation and hard swish activation functions for improved non-linearity.

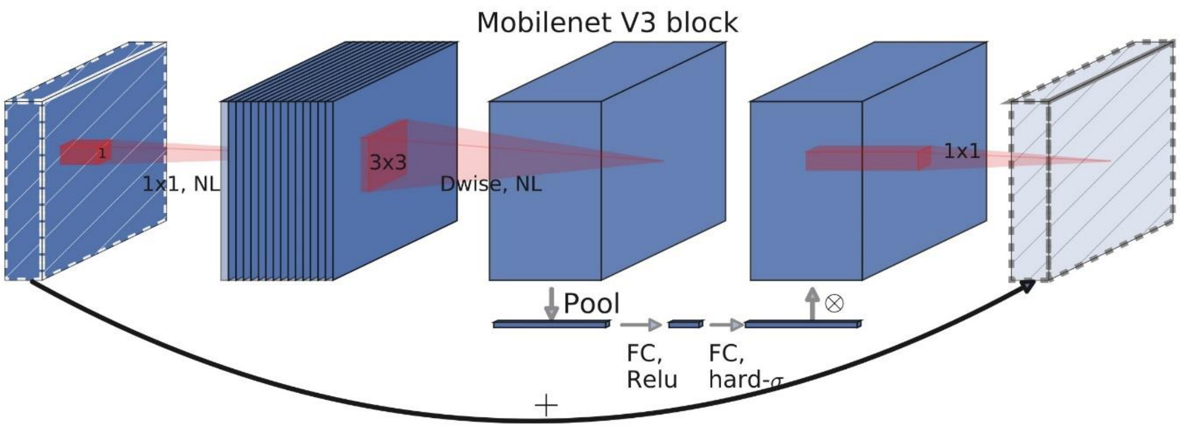


Fig – 2.1 Mobile Net Version 3 Block Diagram

Convolutions can be divided into depth-wise and pointwise convolutions using depth-wise separable convolutions, are used by MobileNetV3 to reduce computing costs. Width and resolution multipliers are also employed to control the model's size and complexity. Modules for squeeze and excitation are also integrated into the network. These modules recalibrate feature maps adaptively by employing completely linked layers following global average pooling. Furthermore, MobileNetV3 uses hard swish activation functions which are defined by a combination of linear and non-linear processes to introduce non-linearity while maintaining computing efficiency.

The cutting-edge convolutional neural network architecture known as Inception-Net, or GoogLe-Net, was developed by Google. It revolutionised the field of deep learning by introducing the concept of inception modules, which execute convolutions of different sizes concurrently and concatenate their outputs to efficiently collect both local and global information. With the use of parallel convolutional pathways with various kernel sizes, Inception-Net achieves remarkably high efficiency in capturing features at several scales. This approach is appropriate for a variety of computer vision applications because it strikes a compromise between computational efficiency and model complexity.
In Fig-2.2 ,Inception Net utilizes inception modules, which consist of multiple convolutional layers of different kernel sizes.

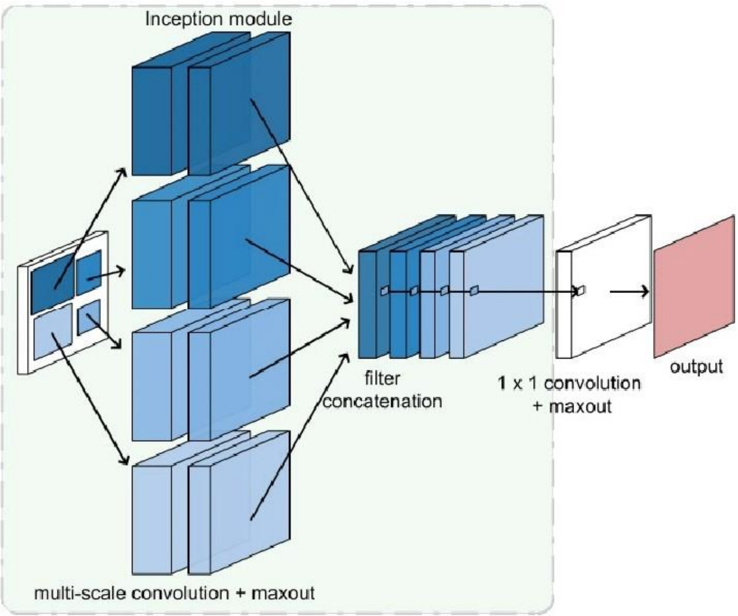


Fig -2.2 Inception Module Diagram

2.3 Use case Analysis

In Fig-2.3, the use case diagram not only delineates the roles of the user and developer but also underscores their distinct access privileges within the application. The user, typically a consumer or seafood industry professional, engages with the system through the utilization of the web camera feature to capture images of fish specimens. These images serve as the primary input for the system's assessment of fish freshness and potential formaldehyde contamination. Conversely, the developer, possessing elevated access rights, assumes responsibility for overseeing the system's functionality, configuration, and administration. This includes tasks such as software updates, troubleshooting, and ensuring the seamless integration of various modules within the application architecture.

Upon capturing the images, the front-end application, acting as the interface for user interaction, facilitates the seamless transfer of image data to the backend machine learning module. Here, sophisticated algorithms, meticulously trained on diverse datasets, undertake the arduous task of analyzing the images to ascertain their freshness status. Through intricate pattern recognition and feature extraction techniques, the machine learning process discerns subtle visual cues indicative of fish freshness, such as skin texture, eye clarity, and overall coloration. If the classification outcome identifies an image as fresh, the application seamlessly progresses to the next stage of assessment. Conversely, if the image is flagged as not fresh, the system may prompt appropriate actions or alerts based on predefined thresholds or user-configured preferences. This adaptive response mechanism underscores the system's versatility and adaptability in addressing diverse scenarios encountered in the assessment of fish products.

In cases where the image is classified as fresh, the system initiates the meticulous process of collecting data on formaldehyde content as an additional safety measure. This critical task is accomplished through seamless interaction with a dedicated sensor integrated into the system's hardware architecture. The formaldehyde sensor, calibrated to detect even trace amounts of the chemical compound, ensures comprehensive scrutiny of fish specimens for potential contamination. Once the formaldehyde data is meticulously collected and analyzed, it is seamlessly relayed back to the front-end application for transparent display to the user. This real-time feedback mechanism empowers consumers and industry professionals with invaluable insights into the safety and quality of the assessed fish products, thereby fostering trust and confidence in the integrity of the assessment process.

In essence, the harmonious integration of image classification, formaldehyde detection, and user interface functionality within the application architecture exemplifies a paradigm shift in ensuring the safety and quality of seafood products. Through meticulous attention to detail, technological innovation, and user-centric design principles, the system transcends conventional boundaries to deliver unparalleled efficiency, reliability, and transparency in the assessment of fish freshness and formaldehyde contamination.

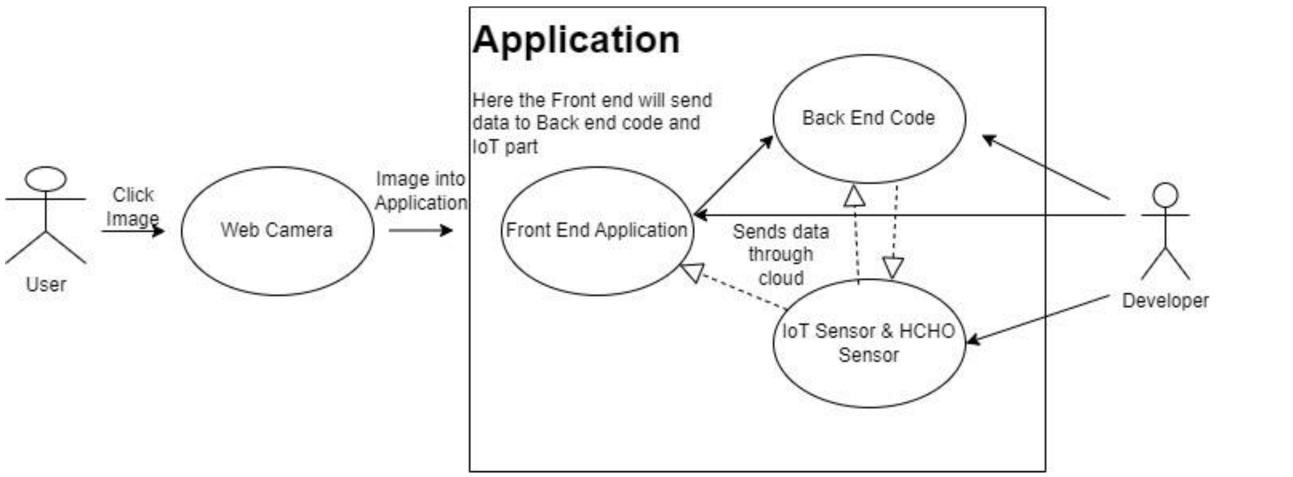


Fig – 2.3 Shows the Use Case diagram for the system

2.4 Requirement Specification

2.4.1 Functional Requirements

Function requirements, also known as functional requirements, outline the specific actions or operations that a system or software application must perform to meet the needs of its users. These requirements describe the functionality or behavior of the system, detailing what it should do to fulfill its intended purpose.

a) Image Capture:

The system should support the functionality to initiate the webcam or similar device to capture images of fish. Users should be able to trigger the image capture process easily from the front-end application with a designated button or interface element. The image capture process should be responsive, ensuring minimal delay between the user's action and the actual capture.

b)Image Transmission:

Captured images should be transmitted securely from the front-end application to the backend machine learning module. The transmission protocol should be efficient, supporting fast data transfer to minimize latency. Error handling mechanisms should be in place to handle transmission failures, ensuring data integrity and reliability.

c)Machine Learning Classification:

The backend module should utilize machine learning algorithms capable of accurately classifying fish images into categories of fresh or not fresh. Training data should be periodically updated to improve the classification accuracy and adapt to changes in fish appearance over time.

The classification process should be optimized for performance, allowing for quick analysis of images without significant computational overhead.

d)Formaldehyde Detection:

Upon classifying an image as fresh, the system should activate the formaldehyde detection process. Interfacing with the formaldehyde sensor should be implemented to collect relevant data on formaldehyde content in the fish samples.

The sensor data should be processed and interpreted accurately to determine the level of formaldehyde present in the fish.

e)Data Display:

Results from both the image classification and formaldehyde detection processes should be presented clearly and intuitively to users through the front-end application. Visual representations such as charts, graphs, or textual indicators may be used to convey the classification results and formaldehyde levels effectively.

The display interface should be responsive and accessible across different devices and screen sizes to accommodate various users' needs.

f)Real-time Processing:

The system should aim to process incoming image data and provide classification results and formaldehyde measurements in near real-time.

Performance optimizations such as parallel processing, caching, or hardware acceleration may be employed to minimize processing delays and improve responsiveness.

g)Scalability:

The system architecture should be designed to scale horizontally or vertically to accommodate increases in user activity and data processing demands. Load balancing mechanisms should be implemented to distribute incoming requests evenly across multiple servers or processing nodes.

Resource allocation should be managed dynamically to ensure optimal performance and resource utilization under varying workloads.

h)Performance Metrics:

For our project, performance metrics encompass accuracy, speed, and resource utilization. Accuracy measures the system's ability to correctly classify fish freshness and detect formaldehyde levels, with sub-metrics such as true positive and false negative rates providing detailed insights. Speed refers to the system's processing time from image capture to result display, aiming for real-time or near real-time performance.

Resource utilization evaluates the efficiency of computational resources like CPU, memory, and storage, ensuring optimal operation and minimal infrastructure costs. Regular monitoring and user access to performance metrics facilitate system optimization and informed decision-making.

2.4.2 Non-Functional Requirements:

a)Performance:

The system should respond promptly to user requests, providing real-time or near real-time results. It should handle multiple concurrent users efficiently without significant degradation in performance.

b)Reliability:

The system should be highly reliable, with minimal downtime and robust error handling mechanisms in place. It should gracefully recover from failures and ensure data integrity throughout

c)Scalability:

The system should be scalable to accommodate a growing user base and increasing data volumes. It should handle additional load by provisioning resources dynamically and distributing workload effectively across servers.

d)Security:

Data security and privacy are paramount. The system should employ encryption techniques to protect sensitive information during transmission and storage. Access controls should be implemented to restrict unauthorized access to the system and its data.

e)Usability:

The system should have a user-friendly interface, intuitive navigation, and clear instructions for users. It should support multiple devices and screen sizes to ensure accessibility for a diverse user base.

f)Maintainability:

The system should be easy to maintain and update. Code should be well-documented, modular, and adhere to coding standards to facilitate future enhancements and bug fixes.

g)Compatibility:

The system should be compatible with a wide range of devices, browsers, and operating systems. It should also integrate seamlessly with other systems or platforms as needed.

h)Performance Metrics:

The system should define and measure key performance metrics such as accuracy, speed, and resource utilization. Regular monitoring and analysis of these metrics will help identify areas for improvement and ensure optimal system performance.

2.4.3 Hardware Requirements

a)Webcam:

A high-resolution webcam capable of capturing clear images is essential for capturing fish images.

b)Microcontroller Board:

An Arduino Uno or similar microcontroller board is required to interface with the formaldehyde sensor and transmit data to the frontend application.

c)Formaldehyde Sensor:

A formaldehyde sensor capable of detecting and measuring formaldehyde levels in the surrounding environment is necessary to ensure food safety.

d)Computer:

A computer or server is needed to host the frontend application and backend machine learning algorithms. It should have sufficient processing power and memory to handle image processing and classification tasks efficiently.

e)Network Connectivity:

Stable internet connectivity is essential for transmitting data between the frontend application, backend server, and external sensors.

f)Storage:

Sufficient storage space is required to store captured images, machine learning models, and sensor data.

g)Display Device:

A display device such as a monitor or smartphone is needed to view the frontend application and display results to the user.

2.4.4 Software requirements

a)Python Development Environment:

A Python development environment is necessary, including the Python interpreter and a code editor such as Visual Studio Code, PyCharm, or Jupyter Notebook.

b)Machine Learning Frameworks:

Python libraries like TensorFlow, PyTorch, or scikit-learn are essential for implementing and training machine learning models for fish freshness classification.

c)Image Processing Libraries:

The OpenCV library in Python provides extensive support for image processing tasks, including preprocessing and feature extraction from the captured fish images.

d)Web Framework:

A Python-based web framework such as Flask is required to develop the backend server that hosts the machine learning models and handles communication with the frontend application.

e)Anaconda Distribution:

Anaconda provides a comprehensive Python distribution that includes popular data science libraries, such as NumPy, Pandas, and Matplotlib, along with the Conda package manager. It serves as the primary environment for developing and running Python code, managing packages, and creating virtual environments.

f)Deep Learning Frameworks:

Deep learning frameworks like TensorFlow or PyTorch are essential for implementing and training neural network models for fish freshness classification. These frameworks offer high-level APIs for building complex neural networks and provide efficient computation on both CPU and GPU devices.

CHAPTER 3

SYSTEM DESIGN

This System is an innovative solution designed to ensure the freshness and safety of fish products through automated image processing, machine learning, and Internet of Things (IoT) integration. At its core, the system aims to address the critical need for reliable and efficient methods of assessing the freshness of fish, a key factor in ensuring consumer health and satisfaction.

At the forefront of the system is the User, who interacts with the Frontend Application to initiate the process. Using a webcam, the User captures images of fish products, which are then transmitted to the Backend Server for further processing. The Frontend Application serves as the gateway for the User, providing a user-friendly interface for image capture and displaying the results of freshness assessment and formaldehyde detection.

Behind the scenes, the Backend Server hosts a suite of services responsible for processing the images and analysing their freshness. The Image Processing Service employs advanced techniques such as augmentation and segmentation to enhance the quality of the images before passing them on to the Machine Learning Service. Here, the Data Preprocessing component prepares the data for analysis by splitting it into training, testing, and validation sets. The Model Building component utilizes state-of-the-art algorithms such as MobileNetV3 and Inception-Net to construct predictive models capable of classifying fish freshness accurately. The Model Validation component ensures the reliability of the models through rigorous testing and validation procedures.

In parallel, the IoT Integration Service facilitates the collection of formaldehyde data for fish products classified as fresh. Upon detecting fresh fish, the Backend Server triggers the IoT Integration Service to interact with the HCHO Sensor, which measures the formaldehyde level of the fish. The data obtained from the sensor is then transmitted to the Blynk Integration component, which displays the formaldehyde alert on the Frontend Application, providing users with valuable information about the safety of the fish products.

The Developer's role extends beyond mere oversight, as they actively engage in the system's evolution, responding to feedback from both Users and stakeholders. Through continuous monitoring and analysis of system performance metrics, the Developer identifies areas for improvement and implements enhancements to optimize user experience and system efficiency.

Moreover, the system facilitates seamless communication between Users and Developers through feedback mechanisms and support channels. This iterative process fosters a collaborative environment where user input drives ongoing refinement and innovation, ensuring that the system remains responsive to evolving needs and technological advancements.

Furthermore, the Developer leverages advanced analytics and data-driven insights to identify trends, patterns, and anomalies within the system. By harnessing the power of big data and predictive analytics, they can anticipate potential issues and proactively address them before they impact system functionality or user satisfaction. In essence, the symbiotic relationship between Users and Developers forms the cornerstone of the system's success, fostering continuous improvement and innovation. Together, they propel the system towards its overarching goal of ensuring the freshness and safety of fish products, thereby enhancing consumer trust and promoting sustainable practices within the seafood industry.

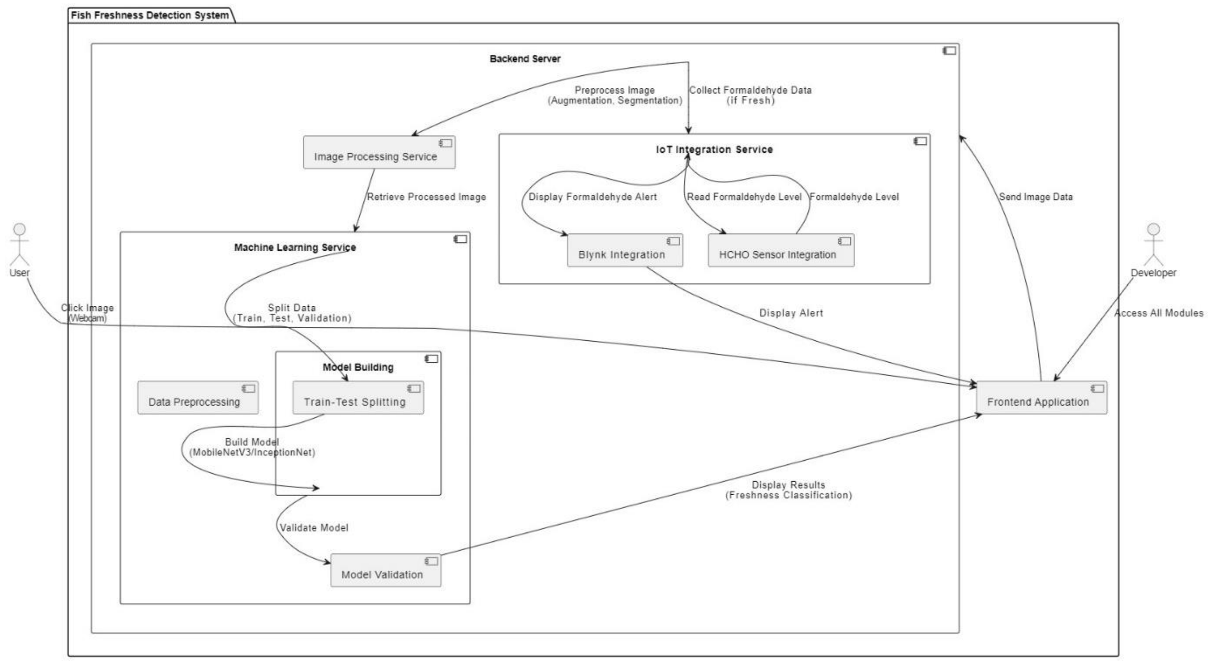


Fig -3.1 Architecture Diagram

a

3.2 Design of methodology

The design of the methodology involves careful planning and execution to ensure the accuracy, efficiency, and reliability of the system's processes.

Below is an outline of the key components of the methodology

a)Data Collection:

The first step in the methodology involves collecting a comprehensive dataset of fish images representing various species, conditions, and freshness levels.

The dataset should include images captured under different environmental conditions and lighting to ensure robustness and generalization of the ML models.

In addition to fish images, relevant metadata such as species, weight, and source may also be collected to enrich the dataset and facilitate analysis.

b)Preprocessing and Augmentation:

Once the dataset is assembled, preprocessing techniques are applied to standardize the images and remove any noise or inconsistencies.

Augmentation methods such as rotation, flipping, and resizing may be employed to increase the diversity of the dataset and improve the robustness of the ML models.

Data augmentation helps address issues such as overfitting and ensures that the ML models can accurately classify fish images under various conditions.

c)Model Building and Training:

With the pre-processed and augmented dataset, ML models are built using deep learning architectures such as MobileNetV3 and Inception-Net.

The dataset is split into training, validation, and test sets to train and evaluate the performance of the ML models.

During the training phase, the ML models learn to classify fish images into categories such as fresh and non-fresh based on features extracted from the images.

d)Model Evaluation and Validation:

Following training, the ML models are evaluated using the validation dataset to assess their performance metrics such as accuracy, precision, recall, and F1 score.

Cross-validation techniques may be employed to ensure the robustness of the models and mitigate issues such as overfitting.

The ML models are validated against real-world scenarios and compared against baseline models or industry standards to ensure their effectiveness in fish freshness classification.

e)IoT Integration and Chemical Detection:

In parallel with the ML model development, IoT devices such as HCHO sensors are integrated into the system to detect chemical contaminants such as formaldehyde. The IoT devices are calibrated and tested to ensure their accuracy and reliability in detecting formaldehyde levels in fish samples.

Integration with platforms such as Blynk enables real-time monitoring and visualization of formaldehyde levels, providing users with immediate alerts and notifications.

f)Frontend Application Development:

Simultaneously, a user-friendly frontend application is developed to facilitate user interaction and provide seamless access to the system's features.

The frontend application allows users to capture fish images, view freshness classification results, and receive alerts regarding formaldehyde levels. User feedback and usability testing are conducted to refine the frontend application and enhance the overall user experience.

g)System Integration and Deployment:

Once all components are developed and tested independently, they are integrated into a cohesive system architecture. System integration involves connecting the frontend application, ML models, and IoT devices to ensure seamless communication and data exchange.

The integrated system is deployed in real-world environments such as fish markets, processing plants, or retail stores, where it undergoes further validation and refinement.

3.3 Modules

3.3.1 Data Collection & Image Processing Module

The Data is collected from various online sources and merged together to make as Fresh and Non-Fresh and Fig – 3.2 Shows the Fresh fish images and Fig – 3.3 Shows the Non-Fresh images.

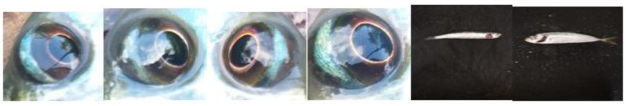


Fig-3.2 Fresh Images

Fig – 3.3 Non-Fresh Images

Collected dataset is used to train the model, while the remaining ten to fifteen percent is used for testing. Once the dataset has been divided, image processing is necessary in order to evaluate and adjust each individual image sample. This process includes several processes designed to improve and extract pertinent data. The photos' aesthetic appeal. Segmentation makes it possible to recognise and distinguish between several items or areas within a picture, which then allows for localised analysis. Feature extraction is the process of identifying relevant characteristics in the images. The Inception and Mobile Net Version 3 algorithms are used to train the model. A thorough description of the software process that we employed to create this system may be seen in “Fig.3.4”. The trained model is integrated into the web application. The fish iris photo is taken using the web application.

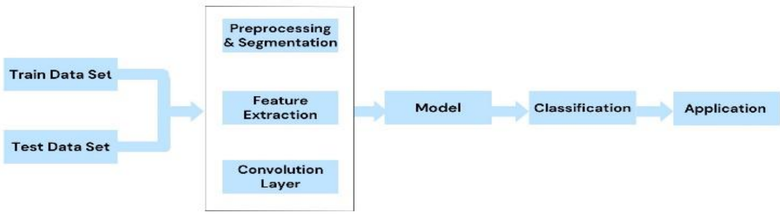


Fig – 3.4 Shows the Image Processing and next steps

3.3.2 Classification module

In addition to analysing the fish's eye, this work also incorporates various preprocessing techniques to enhance the quality and reliability of the image data. Preprocessing steps such as noise reduction, contrast enhancement, and normalization are applied to the captured images before they are fed into the classification model. These preprocessing steps help to standardize the image data and remove any inconsistencies that may affect the accuracy of the classification results.

Furthermore, to ensure the robustness and generalization of the classification model, data augmentation techniques are employed during the training phase. Data augmentation involves artificially generating new training samples by applying transformations such as rotation, scaling, and cropping to the original images. By augmenting the dataset with variations of the original images, the model becomes more resilient to changes in lighting, orientation, and other environmental factors commonly encountered in real-world scenarios.

The choice of using both the Inception Net and Mobile Net Version 3 techniques for training the classification model highlights the emphasis on performance optimization and model efficiency. While the Inception Net architecture excels in capturing complex features and patterns from high-resolution images, the Mobile Net Version 3 architecture is specifically designed for mobile and embedded vision applications, offering a balance between model size, speed, and accuracy. By leveraging the strengths of both architectures, the classification model achieves high accuracy while remaining lightweight and computationally efficient, making it suitable for deployment in resource-constrained environments such as mobile devices or edge devices.

Additionally, the process of updating the model in the Web Application ensures that the classification system remains adaptive and responsive to changes in the underlying data distribution. Regular updates to the model enable it to adapt to new patterns and variations in the fish images, improving its performance over time. This iterative approach to model refinement is essential for maintaining the system's effectiveness and reliability in classifying fish freshness accurately and efficiently.

In Fig 3.5 shows Overall combination of advanced image processing techniques, data augmentation strategies, and state-of-the-art deep learning architectures contributes to the development of a robust and reliable classification system for assessing fish freshness. By leveraging the latest advancements in computer vision and machine learning, this work aims to enhance food safety standards and ensure the quality and integrity of fish products in the market.

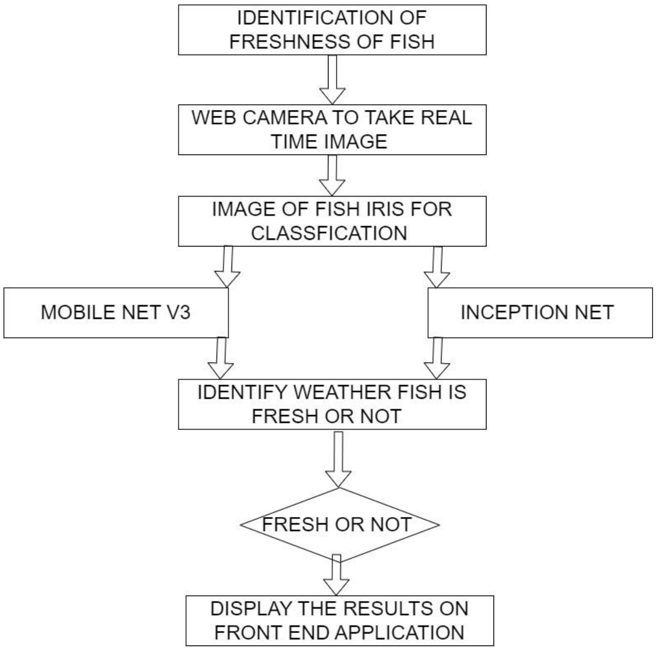


Fig – 3.5 Classification Module

3.3.3 Hardware Module

In addition to the Arduino UNO and HCHO Gas Sensor, the hardware setup also includes additional components to facilitate seamless communication and data transfer. The Arduino UNO serves as the central processing unit, orchestrating the collection of formaldehyde data from the HCHO Gas Sensor and managing the transmission of this data to external systems. The HCHO Gas Sensor, based on semiconductor technology, offers high sensitivity and stability, enabling accurate detection of formaldehyde levels in the surrounding environment. Its conductivity varies with the concentration of volatile organic compounds (VOCs) present in the air, providing real-time feedback on air quality.

To visualize and analyse the formaldehyde content, the Arduino UNO is connected to the Grove formaldehyde sensor, which provides a user-friendly interface for monitoring and interpreting sensor readings. The hardware setup, illustrated in detail in Figure 3.6 , showcases the integration of these components into a cohesive system.

The microcontroller embedded within the Arduino UNO is programmed to trigger notifications on an Android application display whenever formaldehyde is detected outdoors. This feature enhances user awareness and safety by providing timely alerts regarding potential health risks associated with high formaldehyde levels in the environment. Moreover, the Arduino UNO is equipped with a WIFI module, enabling seamless connectivity to the internet and cloud-based storage platforms.

Through the WIFI module, sensor data is transmitted to cloud storage, where it is securely archived and accessible for further analysis and monitoring. Additionally, the data is relayed to the Blynk app, a versatile mobile application that offers intuitive visualization tools and customizable dashboards for tracking environmental parameters. By leveraging cloud-based infrastructure and mobile connectivity, the hardware setup ensures the seamless integration of formaldehyde monitoring capabilities into everyday environments, promoting user safety and environmental awareness.

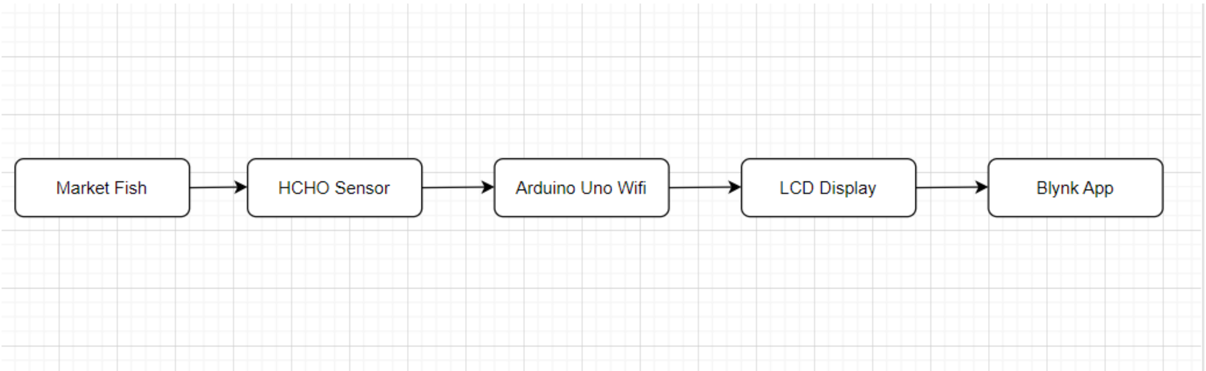


Fig – 3.6 Flow of Hardware Module

3.3.4 User Interface Module

The Frontend Application Module serves as the user interface for interacting with the Fish Freshness Detection System. Implemented using Flask, a Python web framework, this module seamlessly integrates HTML files with the backend functionalities, facilitating user interaction with the system. Through the web interface, users can easily upload images captured from webcams for processing by the system. Upon submission, the images are forwarded to the backend for analysis of fish freshness using machine learning algorithms.

Once processed, users can conveniently view the results directly on the web interface, which includes detailed information regarding the freshness classification of the fish.

In cases where the fish is classified as fresh, the system initiates the collection of formaldehyde data using IoT integration. This process is seamlessly executed through the web interface, providing users with real-time insights into the formaldehyde content of the fish.

Overall, the Web Interface Module offers an intuitive and user-friendly platform for users to interact with the Fish Freshness Detection System. By providing access to key functionalities such as image uploading, result visualization, and IoT integration, the module empowers users to make informed decisions regarding the freshness and safety of fish products. Through its intuitive design and seamless integration with backend services, the Web Interface Module enhances the overall user experience and promotes efficient utilization of the system's capabilities for fish quality assessment.

CHAPTER IV

SYSTEM IMPLEMENTATION

4.1 Module Implementation

System implementation involves translating the design specifications of the Fish Freshness Detection System into a functional and operational system. This phase encompasses the development and integration of various modules, including the frontend application, backend server, machine learning module, and IoT integration module. Each module is implemented according to predefined requirements, utilizing appropriate technologies and frameworks. System implementation also involves rigorous testing to ensure that each component functions as intended and interfaces seamlessly with other modules. Throughout this process, close attention is paid to performance optimization, scalability, and reliability to deliver a robust and efficient system.

Module implementation focuses on the development and deployment of individual modules that collectively form the Fish Freshness Detection System. These modules are designed to perform specific tasks, such as image processing, machine learning classification, and IoT data collection. In our project, the main modules are the Frontend Application Module and the Backend Server Module.

The Frontend Application Module provides a user-friendly interface for uploading images and viewing freshness classification results, while the Backend Server Module handles image processing, machine learning inference, and IoT integration. Each module undergoes thorough development, testing, and refinement to ensure its functionality and interoperability within the larger system architecture. Through meticulous module implementation, our project delivers a comprehensive solution for fish quality assessment that meets the needs of users effectively and efficiently.

Furthermore, system implementation involves adhering to best practices in software engineering, such as modular design, version control, and documentation. Collaboration between developers, designers, and domain experts ensures that the implemented system aligns closely with user requirements and industry standards.

Continuous feedback and iteration are essential throughout the implementation phase to address any issues or enhancements promptly. Overall, a systematic and disciplined approach to implementation is critical to the success of the Fish Freshness Detection System, enabling it to deliver accurate, reliable, and user-friendly functionality for assessing fish quality and ensuring food safety.

4.1.1 Classification Module Implementation

In the software module implementation of our Fish Freshness Detection System, the image preprocessing begins with the reception of raw images from the webcam in the frontend application. These images undergo preprocessing steps such as augmentation and segmentation to enhance their quality and extract relevant features. Once pre-processed, the images are forwarded to the backend server, where they undergo the train-test split process. This involves dividing the dataset into separate subsets for training, validation, and testing purposes to evaluate the performance of the machine learning models.

After the train-test split, the pre-processed images are fed into the machine learning module, where they undergo classification using two different algorithms: MobileNetV3 and Inception-Net. In the implementation, the images are processed through both algorithms simultaneously to compare their performance and determine the most suitable model for freshness classification. MobileNetV3 and Inception-Net are integrated into the system architecture to handle image classification tasks efficiently and accurately.

Once the image classification is complete, the results are communicated back to the frontend application for display to the user. Simultaneously, if the classification indicates that the fish is fresh, the backend server initiates communication with the IoT integration module to collect formaldehyde data. This involves querying the HCHO sensor to measure the formaldehyde level

In real-time operation, the Fish Freshness Detection System collects data continuously from various sources, such as image inputs and IoT sensors, to ensure prompt and accurate assessment of fish quality. The collected data undergoes rapid processing and analysis within the backend server module, where sophisticated algorithms handle tasks such as image classification for freshness and detection of formaldehyde content.

Once the analysis is complete, the results are swiftly transmitted back to the frontend application for immediate display to the user. This seamless integration and real-time data transmission facilitate effective communication between the software modules and enable users to access comprehensive information about the fish's freshness status and formaldehyde content in a timely manner.

In Fig – 4.1, the Classification Implementation in real-time illustrates how the flow of data occurs within the module. It demonstrates the seamless interaction between the frontend application, backend server, and other system components, showcasing the efficient processing and transmission of data for rapid assessment and presentation to the user.

Through this real-time implementation, our system empowers users with valuable insights into fish quality, enabling them to make informed decisions regarding consumption or handling. By ensuring timely access to critical information, we enhance food safety standards and consumer confidence in the seafood industry.

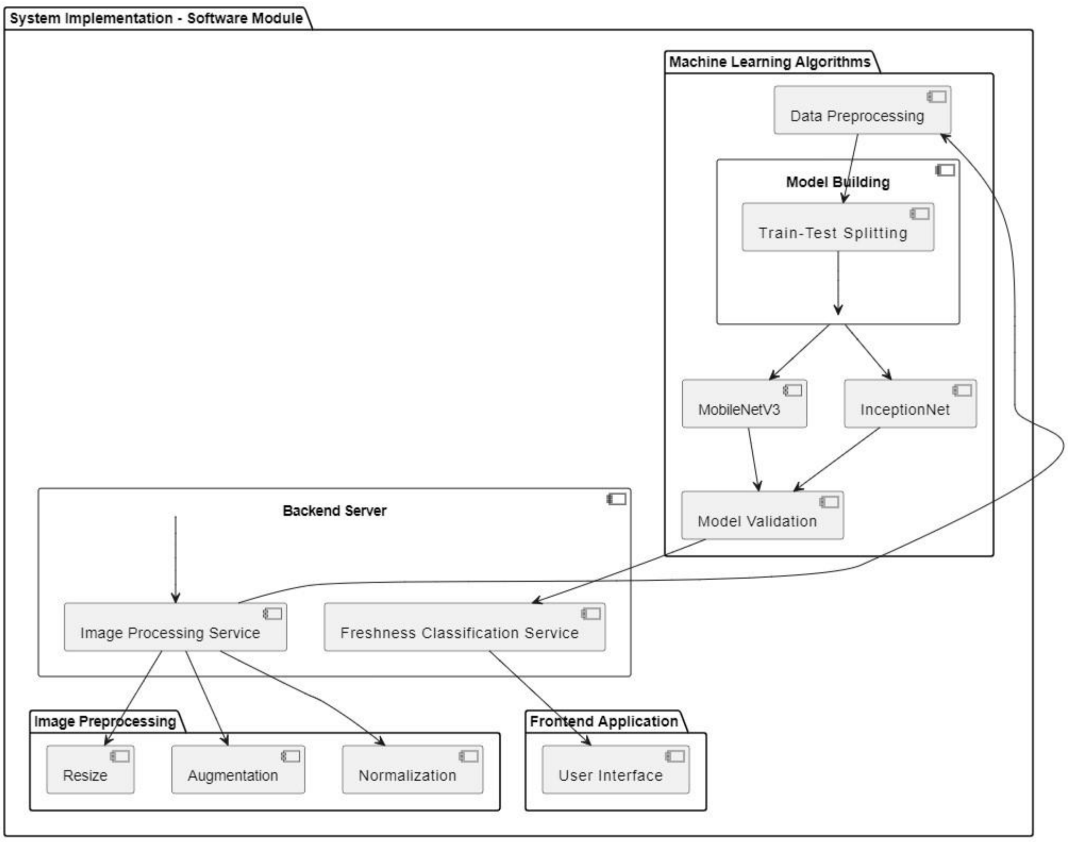


Fig – 4.1 Software Module Implementation

4.1.2 Hardware Module Implementation

The hardware module implementation involves the integration of physical components such as the Arduino Uno microcontroller and the HCHO gas sensor to collect and transmit data in real-time. When the HCHO sensor detects formaldehyde in the surrounding air, it sends corresponding voltage signals to the Arduino Uno. The Arduino Uno processes these signals and converts them into digital data, which is then transmitted wirelessly using a Wi-Fi module.

Upon receiving the digital data, the Wi-Fi module establishes a connection to the internet and transfers the data to cloud storage. This ensures that the formaldehyde level measurements are securely stored and accessible from anywhere. Additionally, the data is relayed to a Blynk application, which provides a user-friendly interface for visualizing and monitoring the formaldehyde levels in real-time.

In Fig – 4.2 shows Overall the hardware module implementation enables seamless data collection and transmission, allowing users to remotely monitor the formaldehyde levels and receive timely alerts if any abnormal levels are detected. This real-time monitoring capability enhances food safety and ensures the freshness of the fish being evaluated.

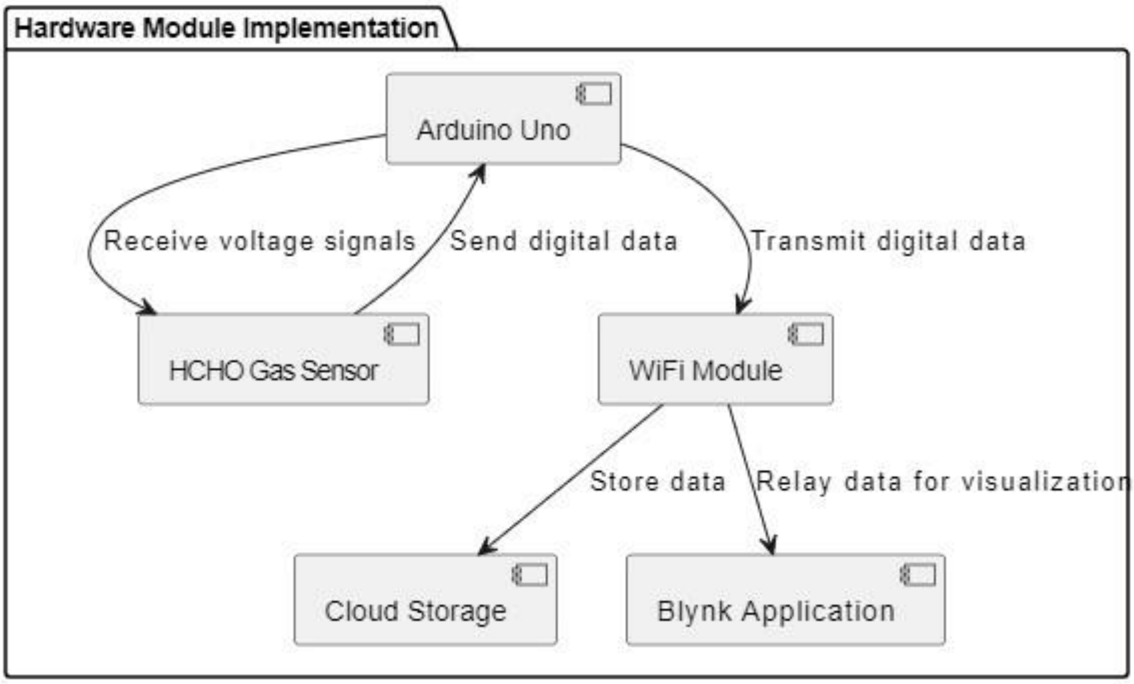


Fig – 4.2 Hardware Module Implementation

4.1.3 User Interface Module Implementation

The frontend application provides a user interface for users to interact with the system seamlessly. Implemented using modern web technologies like HTML, CSS, and JavaScript, it offers a visually appealing and intuitive platform for users to upload fish images captured from a webcam. Upon receiving the image data, the frontend application sends it to the backend server for further processing.

Additionally, the frontend application displays the results obtained from the backend server, indicating whether the fish is classified as fresh or not. This real-time feedback allows users to quickly assess the freshness of the fish. Furthermore, if the fish is classified as fresh, the frontend application triggers the integration with the IoT module to collect formaldehyde data using an HCHO sensor.

In Fig – 4.3, Overall the frontend application serves as a crucial component in the system, enabling users to interact with the detection and classification process effortlessly. Its real-time capabilities facilitate timely decision-making and enhance the overall user experience.

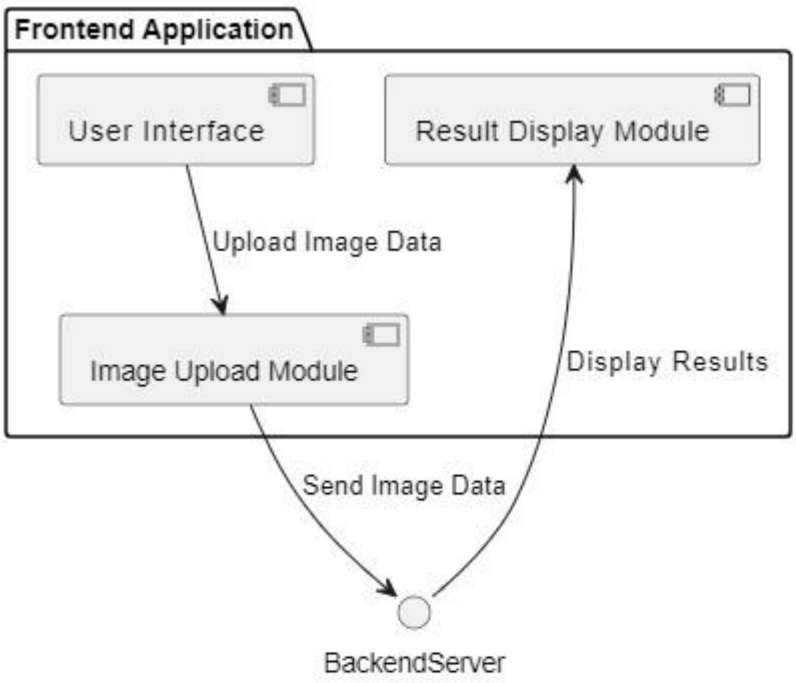


Fig – 4.3 Front End Module Implementation

4.2 Testing

During the testing phase, we thoroughly evaluated each hardware and software component to ensure proper functionality and integration within the Fish Freshness Detection System. Here's a summary of our testing activities:

4.2.1 Hardware Testing:

a)Webcam:

We verified that the webcam captured images effectively and transmitted them to the frontend application without any distortions or delays.

b)Arduino Uno Microcontroller:

The Arduino Uno was tested to ensure proper connectivity and communication with the HCHO gas sensor. We confirmed that it accurately collected data from the sensor and transmitted it to the backend server.

c)HCHO Gas Sensor:

The functionality of the HCHO gas sensor was verified by exposing it to different concentrations of VOC gas. We validated its ability to detect formaldehyde levels accurately and consistently.

4.2.2. Software Testing:

a)Frontend Application (Flask):

We conducted extensive testing of the frontend application developed using Flask to assess its user interface, responsiveness, and functionality. We verified that users could interact with the application seamlessly and that it displayed results accurately.

b)Backend Server (Python Flask):

The backend server, implemented with Python Flask, was tested to ensure it processed incoming image data, interfaced with machine learning algorithms, and integrated with IoT devices efficiently.

c)Machine Learning Algorithms (Anaconda):

We tested the machine learning algorithms implemented in Python using Anaconda to classify fish freshness based on image analysis. The algorithms were evaluated for accuracy, speed, and robustness using test datasets.

d)IoT Integration (Blynk):

Integration with the Blynk app for IoT communication was validated to ensure real-time data transmission between the system and IoT devices. We verified that formaldehyde levels detected by the HCHO gas sensor were accurately displayed on the Blynk app.

4.3.3. Test Data Validation:

We used datasets for training and testing machine learning models to validate their performance and accuracy. The datasets were carefully curated to include diverse samples of fish images representing different freshness levels. Simulated real-time data was generated to test IoT integration, allowing us to assess the system's ability to handle dynamic data streams and respond appropriately in real-world scenarios. Overall, thorough testing of hardware, software, and test data validated the functionality, performance, and reliability of the Fish Freshness Detection System. Any issues or discrepancies identified during testing were addressed promptly to ensure the system's readiness for deployment.

CHAPTER 5

RESULTS AND DISCUSSION

The assessment of fish freshness is a multifaceted process that involves analysing various visual attributes of the fish. Image processing techniques play a pivotal role in this endeavor, enabling the system to extract meaningful features such as skin texture, eye clarity, and overall color. By meticulously examining these attributes, the system can accurately gauge the freshness of the fish, providing businesses and consumers with reliable information about the quality of seafood products. Furthermore, the utilization of machine learning algorithms, including the Inception Net and Mobile Version 3 models, enhances the accuracy of freshness classification. Through extensive training on large datasets, these models can effectively distinguish between fresh and less fresh fish, contributing to the overall robustness of the system.

In addition to assessing fish freshness, detecting the presence of formaldehyde coating on seafood is of paramount importance for ensuring food safety. Formaldehyde, a toxic chemical sometimes used to preserve fish, poses serious health risks to consumers if ingested. To address this concern, the project integrates IoT technology in the form of a formaldehyde (HCHO) gas sensor. This sensor continuously monitors the environment surrounding the fish, promptly detecting any traces of formaldehyde. Real-time alerts are then issued to users, enabling them to take immediate action to mitigate potential risks. By incorporating this real-time monitoring capability, the system provides an additional layer of security, bolstering consumer confidence in the safety of seafood products.

User interaction and interface design are crucial aspects of the project, ensuring accessibility and usability for both businesses and consumers. The inclusion of an LCD display offers a convenient means for users to access information about fish freshness and formaldehyde detection directly. Through intuitive graphical interfaces, users can easily interpret the results and make informed decisions regarding the quality and safety of seafood products. Furthermore, the web application serves as a comprehensive platform for presenting detailed reports, historical data, and user preferences. This centralized hub facilitates seamless communication between the system and its users, fostering transparency and trust in the assessment process.

The project's innovative approach lies in its seamless integration of hardware and software components, leveraging cutting-edge technologies to address critical food safety concerns. By combining image processing, machine learning, and IoT capabilities, the system offers a holistic solution for enhancing food quality standards in the seafood industry. Through continuous refinement and optimization, the project demonstrates a commitment to advancing food safety practices and safeguarding consumer health. Overall, this project exemplifies the transformative potential of technology in ensuring the safety and quality of food products, paving the way for a more secure and sustainable food supply chain.

5.1 Comparision of Machine Learning Algorithms

Here we have used Mobile net version 3 and Inception net algorithms here are the Accuracy response of two algorithms. Fig – 5.1 , shows the graphical representation of Accuracy Response.

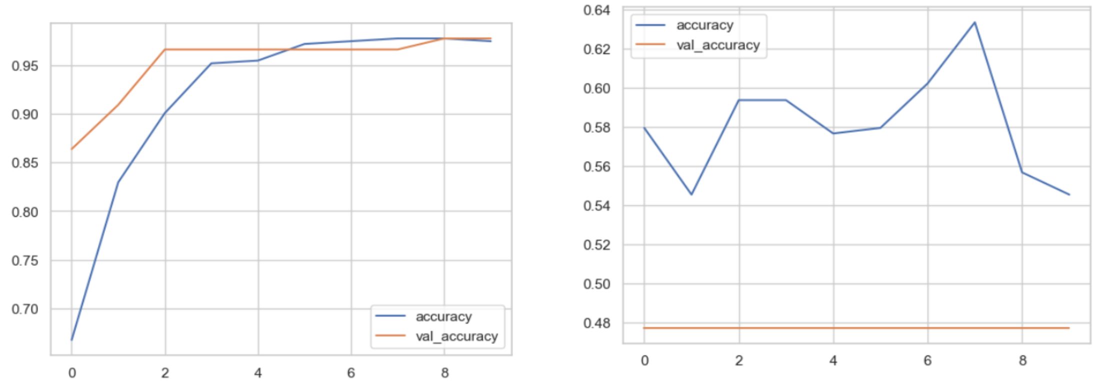


Fig – 5.1 Accuracy Response of Mobile Net V3 & Inception Net Algorithms

In Fig – 5.2 , shows the Training and validation loss which indicate with loss values decreasing and stabilizing as epochs progress.

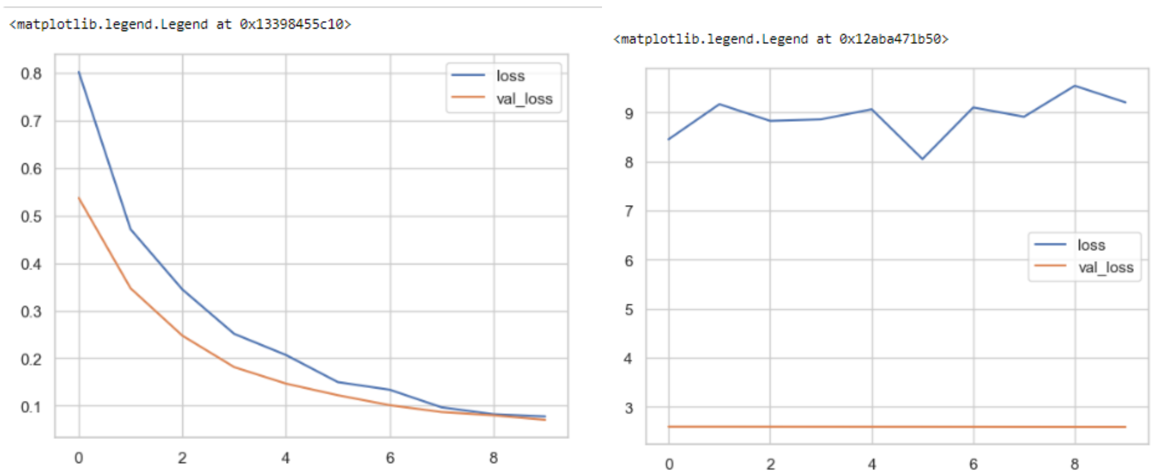


Fig – 5.2 , Shows the training and validation loss of Mobile Net V3 & Inception Net

Confusing Matrix It is a table that shows how well a categorization model performs. A confusion matrix can be used to calculate the accuracy, recall, and precision of the machine-learning system. The algorithm's accuracy refers to how well it will categorise the information.

The formula for accuracy is TP + TN/TP + TN + FP + FN, as displayed in Table I.

Table I Table of Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

Precision is described as the proportion of correctly predicted positives to all predicted positives. Out of all the positive anticipated values, precision indicates the proportion of actually positive forecasts. TP/TP + FP equals precision.

The percentage of accurate positive forecasts to all positives is known as recall. The percentage of the total positive that is projected to be positive is known as the recall.

TP/TP + FN = Recall

The F1 Score is represented by the using precision score and recall score which is done using multiply it with 2

2 * (Precision *Recall / Precision + Recall)

- True Positive, or TP, denotes an accurate prediction of positive values by the algorithm.
- The algorithm's precise forecast of a negative integer is known as True Negative, or TN for short.
- Data that is genuinely negative is forecasted as positive by an algorithm, a phenomenon known as false positive, or FP for short.
- When an algorithm forecasts negative data when it is actually positive, the result is known as false negative, or FN.

In "Fig.5.3" shows the confusion matrix for both Mobile net version 3 algorithm and Inception net algorithm.

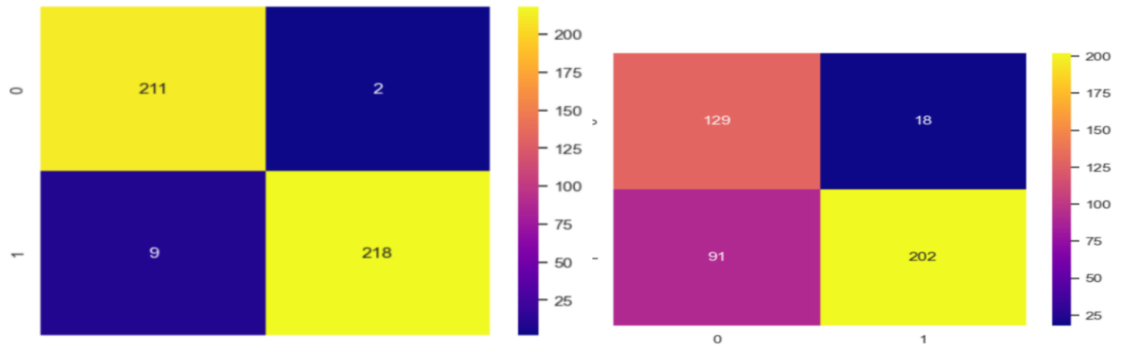


Fig – 5.3 Shows the Confusion Matrix of Mobile Net V3 and Inception net

The Tabel – II Shows the Accuracy , Precision , R1 Score and F1 Score comparision of two Algorithms.

Table – II Comparison Between to Algorithms.

Algorithm	**Algorithms Comparison**			
	Accuracy	***Precision***	***R1 Score***	***Fi Score***
Mobile net V3	98.2 %	0.975	0.975	0.975
Inception Net	75.22 %	0.7522	0.802	0.7592

5.2 Performance Analysis Between two algorithms:

Two compare performance between two algorithm we have several graphs which will represent the comparison between two algorithms.

Fig – 5.4 , The ROC curve illustrates the trade-off between true positive rate and false positive rate for different classification thresholds.

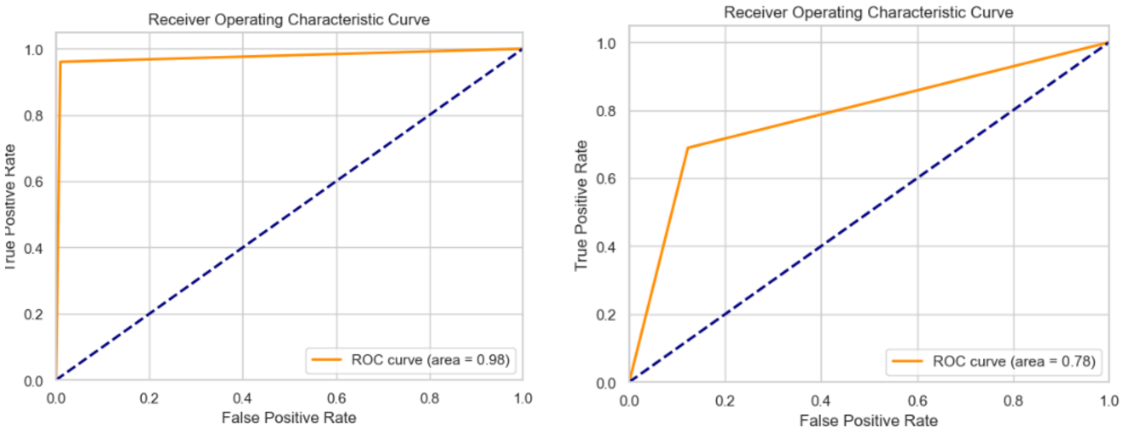
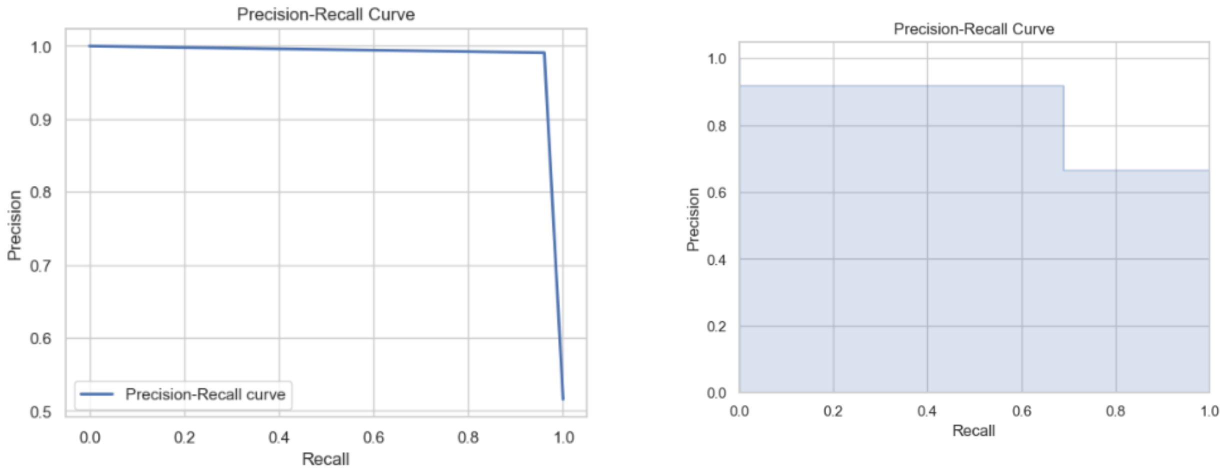


Fig – 5.4 , ROC Curve for two Algorithm

In Fig – 5.5 , The precision-recall curve illustrates the trade-off between precision and recall for different thresholds of a classification model.




```
Average Precision Score: 0.9720764917901482
```

Fig – 5.5 , Shows the Precision – Recall Curve for both Algorithms

5.3 Hardware Results:

In Fig – 5.6, the real-time implementation and setup of hardware components showcase the physical deployment and configuration of the system's IoT infrastructure. This includes the placement and connection of sensors, such as the formaldehyde (HCHO) gas sensor, within the environment where fish are stored or processed. Additionally, it illustrates the integration of microcontrollers or single-board computers, such as Arduino or Raspberry Pi, which serve as the interface between the sensors and the backend software system. Through meticulous setup and calibration, the hardware components are orchestrated to seamlessly capture data and transmit it to the backend for analysis and interpretation.

Moving on to Fig – 5.7, it provides a visual representation of gas detection displayed on the LCD screen, offering real-time insights into the formaldehyde content present in the vicinity. This interface serves as a crucial tool for monitoring and managing potential contaminants, enabling users to take immediate action in response to detected anomalies. Furthermore, the depiction of the same data on the Blynk app emphasizes the system's accessibility and versatility, as users can conveniently access critical information remotely via their smartphones or other devices connected to the internet. This dual display approach enhances the system's transparency and usability, ensuring that users can stay informed and responsive to evolving conditions affecting fish quality and safety.

Additionally, these figures highlight the seamless integration between hardware and software components, showcasing the synergy between physical sensors and digital interfaces in providing comprehensive monitoring and control capabilities. By combining real-time data acquisition with user-friendly visualization, the system empowers users with actionable insights, enabling proactive measures to maintain optimal conditions for fish freshness and mitigate potential risks to food safety. Overall, Fig – 5.6 and Fig – 5.7 exemplify the practical implementation and tangible benefits of the Fish Freshness Detection System in real-world settings, demonstrating its efficacy in safeguarding food quality and consumer well-being..

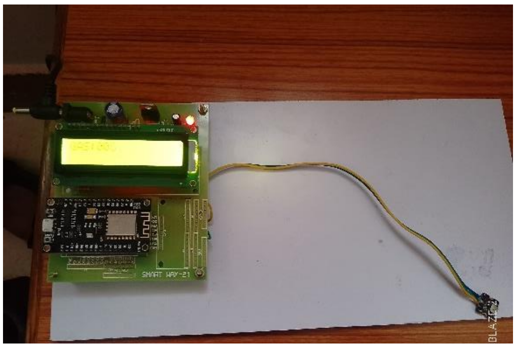


Fig – 5.6 , Hardware Implementation

Fig – 5.7 Gas Detection and Display in the screen.

5.4 Overall Application Output:

Fig.5.8, The most accurate model for estimating food freshness has been employed. Due of its best accuracy, we have linked Mobile Net V3 for front-end prediction. You only need to click on the image to determine whether the food is fresh or not. The model will do the rest. It will display a message stating that it isn't fresh. And if it is fresh then it will show the that it is fresh.

Fig – 5.8 , Front End Overall Application Output

CHAPTER VI

CONCLUSION AND FUTURE SCOPE

In conclusion, the Fish Freshness Detection System presented in this study stands as a comprehensive solution to address the critical challenges surrounding fish quality and safety. Leveraging state-of-the-art technologies such as machine learning and IoT, the system offers users an efficient and dependable method for assessing fish freshness and identifying potential contaminants like formaldehyde.

The comparative analysis between the Inception Net and MobileNetV3 models underscores the system's capability to deliver precise and timely results, empowering consumers to make informed choices regarding their seafood purchases.

Looking forward, there exist abundant opportunities for further advancement and expansion of the system. Firstly, ongoing research and development endeavors could concentrate on fine-tuning the machine learning algorithms to enhance their accuracy and resilience across diverse fish species and environmental conditions.

Additionally, the integration of additional sensors and data sources could augment the system's functionalities, enabling comprehensive monitoring of fish quality indicators and contaminant levels.

Furthermore, incorporating mechanisms for user feedback and crowd-sourced data collection could facilitate continuous refinement and optimization of the system based on real-world usage and evolving consumer preferences.

Furthermore, the scalability and adaptability of the system make it well-suited for deployment in various settings, including seafood markets, processing facilities, and regulatory agencies. By fostering collaboration and knowledge-sharing among stakeholders such as fishermen, retailers, and government bodies, the system has the potential to instigate positive transformation throughout the seafood supply chain, ultimately benefiting both consumers and industry stakeholders alike.

Overall, the Fish Freshness Detection System signifies a significant leap forward in food safety technology and holds immense promise for ensuring the availability of safe, premium-quality seafood for generations to come.

APPENDIX A

SOURCE CODE

Sample Training Source Code:

```
input_tensor = Input(shape=(100,100, 3))

base_model = InceptionV3(input_tensor=input_tensor, weights='imagenet', include_top=False)

x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(2048, activation='relu')(x)
x = Dropout(0.25)(x)
x = Dense(1024, activation='relu')(x)
x = Dropout(0.2)(x)
predictions = Dense(1, activation='sigmoid')(x)

model = Model(inputs=base_model.input, outputs=predictions)

for layer in base_model.layers:
   layer.trainable = False



datagen = ImageDataGenerator(
        rotation_range=10,
        zoom_range = 0.1,
        width_shift_range=0.1,
        height_shift_range=0.1,
        horizontal_flip=False,
        vertical_flip=False)
```

```
datagen.fit(X_train)

epochs = 10

mout = model.fit(X_train, y_train,validation_data=(X_test, y_test), epochs=epochs,batch_size=32,verbose=1)
```

Sample Front End Code:

```
lmt=200

root = Tk()


model=load_model('out.h5')

clss=' GOOD FISH '

root.title('Camera App')

root.configure(bg='#58F')


cap= cv.VideoCapture(0)

if (cap.isOpened() == False):

  print("Unable to read camera feed")



def predict(in_path):

  img = load_img(in_path, target_size = (100,100,3))

  img = img_to_array(img)

  img = np.expand_dims(img,axis=0)

  p = model.predict(img,verbose=0)

  answer=round(p[0][0])

  if answer==0 :

    clss=' FRESH FISH '

    ql=int(requests.get("https://blynk.cloud/external/api/get?token=Y-vSKtdx3Tr5uSOY1i0VUISYi4y3GSIK&v0").text)

    if(ql>lmt):
```

```
        de="CHEMICALS: HIGH"
    else:
        de="CHEMICALS: LIMITED OR NO TRACE"
    return clss,de,(p[0][0]*100)
  elif answer==1 :
    clss='NON FRESH FISH'
    de="NOT GOOD FOR CONSUMPTION"
    return clss,de,(p[0][0]*100)
def captureImage():
    image=Image.fromarray(img1)
    image.save("img.jpg")

    global panelA, panelB
    path="img.jpg"
    image = cv2.imread(path)
    image=cv2.resize(image,(200,200))
    c,a,k=predict(path)

    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    image = Image.fromarray(image)
    image = ImageTk.PhotoImage(image)

    if panelA is None:
        panelA = Label(image=image)
        panelA.image = image
        panelA.pack(side="left", padx=30, pady=10)

    else:
        panelA.configure(image=image)
        panelA.image = image
```

```
    lbl.configure(text=a)
    Btn1.configure(text="DETECTED : "+ c)
    lbl3.configure(text="ACCURACY : "+str(k)+"%")


def exitWindow():
   cap.release()
   cv.destroyAllWindows()
   root.destroy()
   root.quit()


root.state('zoomed')

f1=LabelFrame(root,bg='red')
f1.place(x=10,y=100)
l1=Label(f1,bg='red')
l1.pack()
f2=LabelFrame(root,bg='red')
f2.place(x=850,y=100)
panelA = Label(f2,bg='red')
panelA.pack()
b1=Button(root,bg='green',fg='white',activebackground='white',activeforeground='green',text='Capture Image ',relief=RIDGE,height=2,width=25,command=captureImage)
b1.place(x=700,y=400)
b2=Button(root,fg='white',bg='red',activebackground='white',activeforeground='red',text='EXIT',relief=RIDGE,height=2,width=20,command=exitWindow)
b2.place(x=1000,y=400)
```

```
#lblm = Label(root, text="FISH QUALITY PREDICTION",font=("Arial", 25), bg='green', fg='yellow')
#lblm.pack(side="top", fill="none", expand="no", padx="10", pady="20")
Btn1 = Button(root, text="",font=("Arial", 15),height=2,width=35, bg='blue', fg='yellow')
Btn1.place(x=700,y=500)
lbl = Button(root, text="",font=("Arial", 15), height=2,width=35,bg='green', fg='white')
lbl.place(x=700,y=650)
lbl3 = Button(root, text="",font=("Arial", 15), height=2,width=35,bg='green', fg='white')
lbl3.place(x=700,y=550)
while True:
    r,img=cap.read()
    if(r==False):
      continue
    img1=cv.cvtColor(img,cv.COLOR_BGR2RGB)
    img=ImageTk.PhotoImage(Image.fromarray(img1))
    l1['image']=img



    root.update()

cap.release()
```

Sample Hardware Code:

```
#define BLYNK_PRINT Serial
#include <ESP8266WiFi.h>
#include <BlynkSimpleEsp8266.h>

#define BLYNK_LATE_ID "TMPL3uftYab-g"
#define BLYNK_TEMPLATE_NAME "chemical"
#define BLYNK_AUTH_TOKEN "Y-vSKtdx3Tr5uSOY1i0VUISYi4y3GSIK"
```

```
char auth[] = BLYNK_AUTH_TOKEN;

char ssid[] = "IOT";
char pass[] = "123456789";

#define gas1 A0
long int gas;
#include <LCD_I2C.h>

LCD_I2C lcd(0x27);
void setup() {
  // put your setup code here, to run once:
  Serial.begin(9600);
  pinMode(gas1,INPUT);
  lcd.begin();
  lcd.backlight();
  lcd.setCursor(0, 0);
  lcd.print("IDENTIFICATION");
  lcd.setCursor(0, 1);
  lcd.print("OF CHEMICAL");
  Blynk.begin(auth, ssid, pass, "blynk.cloud", 80);
  lcd.clear();


}

void loop() {
  // put your main code here, to run repeatedly:
Blynk.run();
gas=analogRead(gas1);
```

```
gas=map(gas,0,1024,0,100);
Serial.print("gas : " );
Serial.println(gas);
Blynk.virtualWrite(V0,gas);
lcd.setCursor(0, 0);
lcd.print("GAS:");
if(gas<=9){lcd.print("00");lcd.print(gas);}
else if(gas<=99){lcd.print("0");lcd.print(gas);}
else if(gas<=999){lcd.print("");lcd.print(gas);}


delay(300);
}
```

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