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Deep Fish Net

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***Abstract*—Ensuring the freshness and safety of fish is vital to maintaining high-quality seafood standards and consumer trust. Traditional methods of fish freshness evaluation such as manual inspection and chemical testing are often subjective, time-consuming and unsuitable for large scale operations. To overcome these limitations, this paper presents Deep Fish Net, an intelligent and non-invasive fish quality monitoring system that integrates sensor data acquisition with deep learning based image analysis.**

The system employs an ESP32 microcontroller as the central control unit, interfacing with multiple sensors including a temperature sensor, ammonia sensor and ultrasonic sensor to monitor environmental conditions affecting fish freshness. A camera module captures real-time images of fish samples on a conveyor belt mechanism driven by DC motors controlled through an L293D motor driver IC. Captured images and sensor data are transmitted to a server where a Convolutional Neural Network (CNN) fine-tuned using MobileNetV2 classifies fish into distinct freshness categories.

Experimental results demonstrate an impressive classification accuracy of 97.50%, outperforming conventional inspection techniques in both speed and reliability. Real time monitoring and alert generation through LED indicators and buzzer notifications are made possible. The proposed Deep Fish Net framework provides an efficient, accurate and scalable solution for automated fish freshness assessment, significantly enhancing food safety, reducing spoilage and improving quality control in seafood processing industries.

I. INTRODUCTION

Fish is one of the most widely consumed sources of protein, but it is also highly perishable. Maintaining its freshness is crucial for ensuring food safety, nutritional value, and consumer satisfaction. Once fish is harvested, enzymatic and bacterial activities begin to degrade its quality, releasing gases such as ammonia and altering temperature dependent characteristics. Therefore, continuous monitoring of these parameters is essential to evaluate freshness and prevent spoilage.

Traditional fish freshness assessment techniques such as manual sensory inspection and chemical testing are labour-intensive, time-consuming, and often unreliable due to human subjectivity. Moreover, these methods are not suitable for real-time or large-scale industrial applications. Hence, there is a strong need for an automated, accurate, and non-invasive system that can continuously monitor fish quality parameters.

The proposed Deep Fish Net system addresses this challenge by integrating IoT based sensors and AI driven image analysis for automated fish quality monitoring. The system uses an ESP32 microcontroller as the central control unit, interfacing with multiple sensors such as a temperature sensor, ammonia sensor, and ultrasonic sensor to collect environmental data relevant to freshness. The ultrasonic sensor also assists in detecting the position of fish samples on a conveyor belt mechanism driven by DC motors through an L293D motor driver IC.

In addition to sensor-based monitoring, a camera module captures real-time images of fish samples. These images are processed by a Convolutional Neural Network (CNN) based on the MobileNetV2 architecture, which classifies the fish into freshness categories. The system provides visual and audible feedback using LED indicators and a buzzer, alerting operators about the detected quality level.

The Deep Fish Net system offers a cost-effective, intelligent, and scalable solution for automated fish freshness detection. By combining sensor data with deep learning-based visual analysis, it ensures high accuracy, reduces human intervention, and improves overall efficiency in seafood processing and quality control operations

II. LITERATURE SURVEY

A. Deep Learning and Image Processing Approach for Fish Freshness Detection

The paper titled Deep Learning and Image Processing Approach for Fish Freshness Detection introduces an intelligent and automated technique for assessing the quality of fish using advanced artificial intelligence (AI) and image analysis methods. The authors identify that conventional fish freshness evaluation methods such as manual inspection or chemical testing are often subjective, inconsistent, labor intensive, and unsuitable for large-scale industrial operations. These methods depend heavily on human expertise and can lead to inaccurate judgments due to fatigue, lighting variations, or environmental factors. To address these limitations, the paper proposes a deep learning-based approach that utilizes Convolutional Neural Networks (CNNs) integrated with image processing to classify fish as fresh or spoiled. The process begins by capturing high-quality images of fish under controlled lighting conditions. These images undergo several pre-processing steps, such as resizing, normalization, and noise reduction, to enhance feature extraction and model performance. The CNN then automatically learns and extracts critical visual features including color changes, surface texture, eye clarity, and skin glossiness that serve as reliable indicators of freshness or spoilage. The study demonstrates that the deep learning model achieves superior accuracy and reliability compared to traditional evaluation techniques. The network's ability to self-learn complex feature representations enables it to consistently differentiate between multiple levels of freshness, even under variable environmental conditions. The authors also report that the system's 4 predictions are both fast and non-destructive, making it suitable for real-time applications. Furthermore, the paper emphasizes the potential for integrating this technology into industrial seafood processing lines. When combined with IoT enabled cameras and sensors, the system could enable continuous and automated monitoring of fish freshness throughout the supply chain from catch to packaging. This would greatly reduce product waste, ensure food safety, and enhance consumer trust in seafood quality In conclusion, the research establishes a solid foundation for developing smart, AI-driven fish quality assessment systems. By combining the power of deep learning with modern image processing, this approach not only improves accuracy and efficiency but also represents a major step forward toward sustainable and intelligent food quality management in the seafood industry.

B. *A novel hybrid system for automatic detection of fish quality from eye and gill colour characteristics using transfer learning technique*

Akgül et al. (2023) introduced an innovative hybrid system designed for the automatic detection of fish quality by analysing the eye and gill colour characteristics of fish. This research highlights how colour changes in these regions serve as strong visual indicators of fish freshness, providing an effective, non-invasive way to assess quality. The study specifically focused on two commercially important fish species anchovy (Engraulis encrasicolus) and horse mackerel (Trachurus trachurus) whose freshness levels are typically evaluated through visual inspection by experts. To overcome the limitations of manual methods, the authors developed a deep learning based hybrid approach that integrates image processing, object detection, and transfer learning. The proposed system operates in two main stages. First, the YOLO-v5 (You Only Look Once version 5) model is employed for region detection, accurately identifying and isolating the eye and gill regions from fish images. This step ensures that only the most relevant parts of the image are used for further analysis, reducing noise and improving the model's focus on freshness-related features. In the second stage, the extracted regions are fed into two advanced convolutional neural network architectures Inception-ResNet-v2 and Exception which are fine-tuned through transfer learning. Transfer learning enables the models to leverage pre-trained knowledge from large scale image datasets, significantly enhancing their performance even with limited fish image data. Among the tested combinations, the YOLO-v5 + Inception-ResNet-v2 hybrid model delivered the highest accuracy, achieving 97.67% for anchovy and 96.00% for horse mackerel. These results outperformed other deep learning architectures tested in the study, proving the robustness and precision of the proposed method. The study's findings confirm that deep learning and transfer learning techniques can effectively replace traditional, subjective freshness evaluation methods. The developed system provides a rapid, objective, and non-destructive solution for determining fish quality, eliminating the need for manual handling or chemical tests. Furthermore, this hybrid approach can be easily integrated into automated inspection systems in seafood processing plants, allowing for real time monitoring of fish freshness during storage, packaging, and distribution. Overall, this research represents a major advancement in AI driven food quality assessment, combining YOLO based object detection with transfer learning based classification to achieve both high accuracy and operational efficiency. The hybrid system not only supports quality assurance in the seafood industry but also lays the groundwork for future intelligent food inspection systems that can enhance safety, reduce waste, and maintain consumer trust.

C. *Implementation of Naïve Bayes for Fish Freshness Identification Based on Image Processing*

The study titled Implementation of Naïve Bayes for Fish Freshness Identification Based on Image Processing‖ by Sabarudin Saputra, Anton Yudhana, and Rusydi Umar (2022) presents a cost-effective and efficient approach for determining the freshness of fish using digital image processing combined with machine learning techniques. The primary objective of this research was to develop an automated system capable of classifying fish into different freshness categories without relying on manual inspection or chemical testing methods. In this work, the authors utilized the Naïve Bayes classification algorithm, a simple yet powerful probabilistic model based on Bayes' theorem, which assumes independence among features. The study mainly focused on analysing the RGB colour components extracted from images of fish eyes, as the colour changes in this region serve as key indicators of freshness. The methodology followed a series of well-defined steps: image acquisition, pre-processing, segmentation, feature extraction, and classification all implemented using MATLAB software. During pre-processing, the images were enhanced and normalized to minimize lighting inconsistencies and background noise. Segmentation techniques were then applied to isolate the eye region, from which colour intensity features were derived for further analysis. A total of 210 images were used in the experimental process, which were divided into training and testing datasets. The Naïve Bayes model successfully 7 classified fish samples into three freshness categories: fresh, partially spoiled and fully spoiled. The system achieved an accuracy of 79.37%, demonstrating its effectiveness in identifying freshness levels despite using a relatively simple algorithm. While the accuracy was slightly lower compared to more complex methods such as k-Nearest Neighbours (k-NN) and Support Vector Machines (SVM), the Naïve Bayes approach proved advantageous due to its low computational complexity, faster execution time, and minimal hardware requirements. The study emphasizes that such lightweight models are particularly suitable for real time or embedded system applications, where processing speed and resource efficiency are crucial. By leveraging basic image processing techniques and a probabilistic classifier, this research demonstrates that reliable freshness detection can be achieved without expensive infrastructure or large datasets. In conclusion, the work by Sabarudin et al. contributes significantly to the advancement of smart food quality assessment systems. The integration of Naïve Bayes with image-based feature analysis provides a non-destructive, economical and easily deployable solution for fish freshness identification. This approach holds potential for future applications in small-scale fisheries, retail environments, and automated inspection systems where simplicity and efficiency are key considerations.

D. *Combining MobileNetV1 and Depth wise Separable convolution bottleneck with Expansion for classifying the freshness of fish eyes*

This introduces an innovative deep learning architecture for evaluating fish freshness based on image analysis of fish eyes. The study emphasizes that the eye region of fish provides crucial visual cues such as colour, clarity and pupil opacity that directly reflect the freshness level. The proposed model aims to automate this evaluation process using an optimized and lightweight convolutional neural network suitable for real time applications and mobile devices. The authors developed a modified version of MobileNetV1, named MobileNetV1 with Bottleneck and Expansion (MB-BE). This enhanced architecture integrates Depth wise Separable Convolution Bottleneck with Expansion (DSC-BE) and Residual Transition (RT) layers to improve the network’s ability to capture detailed visual features while keeping computational requirements low. The depth wise separable convolution technique breaks down traditional convolution operations into two simpler steps: depth wise and pointwise convolutions drastically reducing the number of parameters and improving processing speed. The bottleneck with expansion mechanism allows the model to expand feature maps before compression, improving feature representation without increasing model size, while residual transition layers help maintain stability and reduce vanishing gradient issues during training. The experiment utilized the Freshness of Fish Eyes (FFE) dataset which consists of over 4,000 images representing eight different fish species at varying freshness levels. These images underwent pre-processing and were categorized into freshness classes for training and testing the proposed model. The MB-BE model achieved an accuracy of 63.21%, which, although moderate, outperformed several widely used deep learning architectures such as VGG16, Dense Net and Nas Net Mobile. Importantly the MB-BE model maintained a 9 significantly lower parameter size, making it suitable for mobile and embedded system deployment, where computational resources are limited. The study demonstrates that lightweight CNN architectures, when properly optimized using depth wise separable convolutions and bottleneck expansion layers, can deliver competitive performance for non-destructive fish freshness classification. The reduced complexity allows real-time implementation on portable devices, offering practical advantages for on-site seafood quality inspection in fisheries, markets, and processing plants. In conclusion, this research highlights the effectiveness of designing efficient deep learning models for food quality assessment. The combination of MobileNetV1 with advanced convolutional optimization techniques like DSCBE and RT layers provides a balanced trade-off between accuracy, speed, and computational cost, paving the way for the development of smart, mobile based fish freshness detection systems in the seafood industry.

III. PROPOSED SYSTEM

i. *System Architecture*

The system architecture of Deep Fish Net is designed as an integrated IoT AI framework that enables fully automated fish freshness assessment. At the hardware level multiple sensors and actuators are interfaced with an ESP32 microcontroller, which acts as the central control and communication unit. The ESP32 continuously acquires environmental data from the temperature sensor and ammonia (NH_3) sensor to monitor conditions related to fish spoilage, while an ultrasonic sensor detects the presence and positioning of fish samples on the conveyor belt. Based on ultrasonic feedback the ESP32 precisely controls the conveyor mechanism through an L293D motor driver and DC motors, ensuring accurate positioning of the fish under the camera module.

At the processing level, the camera module captures real-time images of fish samples, which are transmitted to the image processing unit where a Convolutional Neural Network (CNN) fine-tuned using the MobileNetV2 architecture performs freshness classification. This AI module analyses visual features such as colour variation, surface texture, and glossiness to determine the freshness category of the fish. The classification results are sent back to the ESP32, where sensor data and AI outputs are combined to make a final decision. At the output level, the ESP32 activates LEDs for visual indication and a buzzer for audible alerts when spoilage is detected. A regulated DC power supply provides stable voltage to all components, ensuring reliable operation. Overall, the Deep Fish Net system architecture integrates sensing, embedded control, mechanical automation and deep learning-based analysis into a single cohesive platform for efficient, accurate, and non-invasive fish freshness monitoring in seafood processing and storage environments.

Fig 1 : Architecture Diagram

ii. *Hardware Implementation*

a) ESP32 Microcontroller

Acts as the central controller that collects sensor data, controls motors, and manages system operations. Its built in Wi-Fi enables real time data processing and communication.

b) Ultrasonic Sensor

Detects the presence and position of fish on the conveyor belt using distance measurement. Ensures accurate timing for image capture and sensor data collection.

c) Ammonia (NH_3) Sensor

Measures ammonia gas released during fish decomposition. Higher ammonia levels indicate spoilage and help determine freshness.

d) Temperature Sensor

Monitors ambient temperature around the fish samples. Temperature data helps assess spoilage rate and freshness condition.

e) Motor Driver (L293D)

Interfaces between ESP32 and DC motors to control speed and direction. Enables smooth movement of the conveyor belt system.

f) LED

Provides visual indication of fish freshness status. Different LED states represent fresh or spoiled conditions.

g) Buzzer

Generates an audible alert when spoiled fish is detected. Helps operators take immediate action.

h) Camera Module

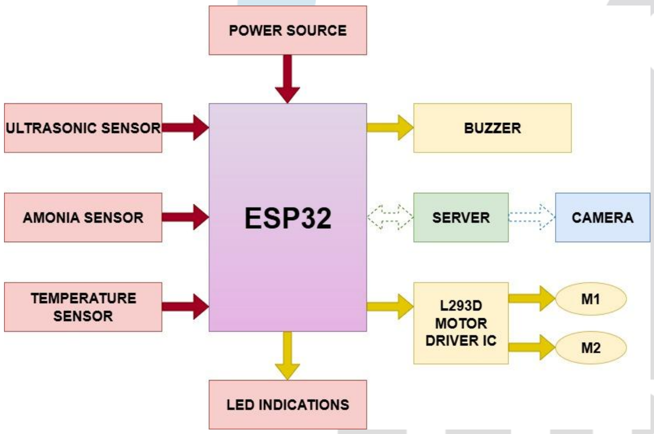
Captures real-time images of fish samples for analysis. Images are processed using a CNN to classify freshness.

i) DC Motors

Drive the conveyor belt that transports fish for inspection. Controlled through the motor driver for precise movement.

j) Power Supply

Provides regulated voltage to all system components. Ensures stable and reliable operation of sensors and controllers. Software Implementation



iii. Software Implementation

The Arduino Integrated Development Environment (IDE) is used for programming and uploading code to the ESP32 boards, providing a simple and user-friendly platform for writing, compiling, and debugging Embedded C/C++ programs. It also supports serial monitoring, which helps developers observe sensor readings, motor operations, and communication responses in real time during testing. Along with this, Embedded C/C++ programming forms the core logic of the system, defining how the ESP32 processes sensor data, controls motors and solenoid valves, and communicates with the Telegram application. By integrating real time decision making, wireless communication, and available libraries for Wi-Fi and motor control, the Arduino IDE and Embedded C/C++ together enable efficient, autonomous operation of IoT based agricultural automation systems.

IV. WORKING METHODOLOGY

The Deep Fish Net operates on the combined principle of sensor-based detection and AI-driven image classification to determine the freshness of fish in an automated and non-invasive manner. The system begins with the ESP32 microcontroller, which acts as the central control unit responsible for coordinating data collection, processing, and output activation. Fish samples are placed on a conveyor belt mechanism powered by DC motors and controlled via the L293D motor driver IC. As the conveyor belt moves, an ultrasonic sensor detects the presence and position of the fish, ensuring that the inspection process is initiated precisely when a sample is in front of the camera module and sensors. Once detection is triggered, the camera module captures high-resolution images of the fish surface, while the temperature sensor and ammonia sensor simultaneously record the surrounding temperature and ammonia gas concentration levels. Temperature monitoring is crucial because higher temperatures accelerate spoilage, while increasing ammonia concentration indicates decomposition and bacterial activity. These readings are transmitted to the ESP32, which then forwards the image data for processing.

The image is analyzed using a Convolutional Neural Network (CNN) model based on the MobileNetV2 architecture, trained to distinguish between different levels of fish freshness. The deep learning model examines visual parameters such as color tone, brightness, eye clarity, and surface texture to categorize the fish as fresh, moderately fresh, or spoiled. Once classification is complete, the ESP32 receives the results and activates corresponding output indicators. LEDs display visual feedback while a buzzer generates an alert sound in case of spoilage detection. Through this integrated approach, the system provides real-time and accurate fish freshness analysis without the need for human inspection. The combination of chemical sensing, visual image processing, and automated mechanical control ensures a fast, reliable, and cost-effective solution for seafood quality monitoring, suitable for fish markets, processing plants and cold storage facilities.

V. CONCLUSION

The proposed Deep Fish Net system introduces a cutting-edge and efficient approach to automated fish freshness detection by combining the power of deep learning, image processing, and IoT based sensor monitoring. Unlike traditional manual or chemical inspection methods, which are often slow, subjective, and destructive, Deep Fish Net provides a non-invasive, intelligent, and real-time solution for evaluating fish quality with high precision. At the core of the system lies a Convolutional Neural Network (CNN) model fine-tuned with MobileNetV2, which processes captured fish images to classify freshness levels accurately. This deep learning approach enhances decision-making by automatically learning key visual features such as texture, colour, and surface appearance factors that human inspectors may find difficult to assess consistently. In addition to image-based analysis, the system integrates temperature and ammonia sensors, which play a vital role in assessing the environmental and biochemical conditions influencing fish freshness. The fusion of these sensor readings with image data significantly improves the reliability and consistency of the freshness predictions. The ESP32 microcontroller acts as the system's central control unit, seamlessly managing sensor data, camera input, and communication with a mobile application through IoT connectivity. This real time data transmission allows users to remotely monitor fish freshness, receive instant alerts via LED and buzzer indicators, and make timely decisions to prevent spoilage and ensure food safety. Overall, the Deep Fish Net system demonstrates the immense potential of AI driven IoT applications in the food industry. It not only enhances the efficiency, accuracy, and scalability of quality inspection but also offers a sustainable and cost-effective alternative to traditional methods. By minimizing human intervention, reducing waste, and promoting transparency in seafood handling, the system contributes significantly to improving food safety standards, reducing post-harvest losses, and strengthening consumer trust in seafood quality.

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