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Revolutionizing Aquaculture with AI: Real-Time Fish Disease Detection and Automated Medication Guidance

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ABSTRACT

Fish disease classification plays a vital role in the sustainability and productivity of seafood aquaculture, especially in India, where the sector contributes significantly to the national economy. Traditionally, disease detection has depended on manual inspection by aquaculture experts through visual examination of fish. However, these methods are often time-consuming and rely heavily on subjective experience, which can result in inconsistencies and delays in diagnosing diseases. To overcome these limitations, recent research focuses on developing automated systems equipped with cameras and sensors to monitor fish health in real time. By incorporating image processing and machine learning techniques, these systems aim to improve the accuracy and speed of disease classification. The integration of such advanced technologies into smart aquaculture systems marks a major step forward in the industry. These innovations not only enhance disease detection and management but also promote sustainable aquaculture by improving operational efficiency, reducing environmental impact, and ensuring better fish welfare.

Keywords: Automated Fish Health Monitoring, Fish Disease Classification, Intelligent Medicine Suggestion, Aquaculture Automation.

1. INTRODUCTION

In Andhra Pradesh, particularly in the Nellore district, aquaculture stands as a vital component of the local economy, significantly contributing to seafood production and food processing industries. However, the sector faces persistent challenges due to fish diseases, which leads to substantial economic losses and impact the livelihoods of fish farmers. To address these issues, there is a growing emphasis on smart aquaculture practices and advanced fish disease detection methods.

Traditional aquaculture in Andhra Pradesh has been plagued by various bacterial and parasitic diseases, leading to increased production costs and decreased yield quality. A study focusing on the region highlighted that diseases are a major concern, particularly bacterial infections, which escalate production costs and diminish both the quality and quantity of yields. In response, the state has initiated measures such as introducing mobile disease diagnosis laboratories to provide on-site assistance to fish farmers, aiming to ensure disease-free aquaculture practices.

The integration of technology into aquaculture, termed 'smart aquaculture,' is revolutionizing fish disease detection and management. Innovations include the use of machine learning algorithms and image processing techniques to monitor fish health in real-time. For instance, intelligent aquaculture monitoring systems have been developed to detect fish diseases early, thereby enabling prompt intervention and reducing mortality rates. These systems analyze physiological data and fish behaviors to identify signs of illness at an early stage, allowing for rapid diagnosis and lowering the risk of disease spread.

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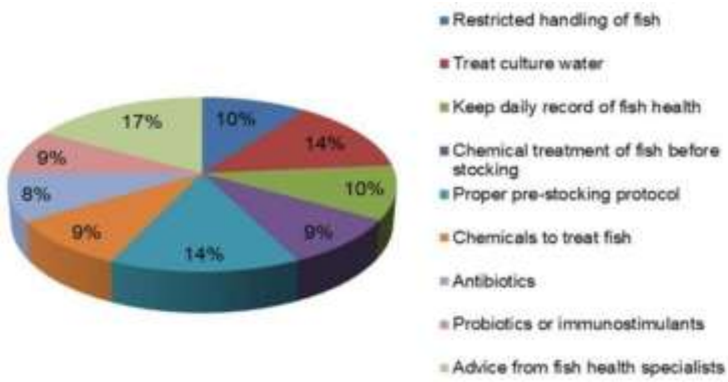

Fig 1: Practical ways to control fish disease

Fish diseases can be classified into different categories based on their causative agents. These classifications help in diagnosing, treating, and preventing diseases effectively in aquaculture and natural water bodies. Classifying fish diseases is crucial for effective diagnosis, treatment, and prevention in aquaculture. Categorizing diseases into bacterial, fungal, viral, and parasitic types enables targeted control strategies. For example, bacterial gill disease requires specific antibacterial treatments, while distinguishing fungal from bacterial infections ensures proper antifungal use. Virus classification aids vaccine development and biosecurity, while identifying parasitic diseases allows for antiparasitic treatments and better management. Overall, disease classification enhances management, improves fish survival, and supports sustainable aquaculture.

2. LITERATURE SURVEY

Arghya Mandal, et al. [16] (2024), They proposed that this abstract provides an overview of the role of AI in fish growth and health status monitoring, emphasizing its significance in promoting a sustainable aquaculture industry. AI technologies, such as machine learning and computer vision, have shown immense potential in analysing large volumes of data collected from fish farms. By leveraging AI algorithms, fish farmers can gain valuable insights into fish growth patterns, feeding behavior, and environmental factors affecting fish health. These algorithms can detect and predict anomalies, diseases, and stress indicators, enabling proactive interventions to mitigate health issues and reduce losses. One of the key applications of AI in aquaculture is the development of smart monitoring systems. These systems employ various sensors, cameras, and data analytics tools to continuously collect real-time data on water quality, temperature, oxygen levels, and fish behavior.

Kailash Bohara, et al. [17] (2024), they proposed that the developments of technologies in aqua medicine, such as sequencing, biosensors and CRISPR, have enabled rapid disease detection within minutes. Furthermore, integrating sensors, drones, artificial intelligence and the internet in aquaculture farm monitoring has helped farmers take decisive actions to improve production. Advancements in diagnostic techniques have significantly enhanced the efficient detection of bacterial, viral, parasitic and fungal diseases in aquatic animals. Moreover, monitoring water quality, aquatic animal health and animal behaviour on farms has become exceptionally streamlined with cutting-edge tools like drones, sensors and artificial intelligence. Summarising research and development in aquatic animal health and monitoring aids efficient technology adoption in aquaculture. With these advanced technologies' continued development and adoption in developed countries, the aquaculture industry is experiencing growth and increased efficiency, benefiting farmers and consumers in these regions.

Yaxuan Zhao, et al. [18] (2024), they proposed that the Phenotypic and behavioral information of fish, which can reflect fish growth and welfare status, play a crucial role in aquaculture management. Stereo

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vision technology, which simulates parallax perception of the human eye, can obtain the three-dimensional phenotypic characteristics and movement trajectories of fish through different types of sensors. It can overcome the limitations in dealing with fish deformation, frequent occlusions and understanding three-dimension scenes compared to the traditional two-dimensional computer vision techniques. With the deep learning development and application in aquaculture, stereo vision has become a super computer vision technology that can provide more precise and interpretable information for intelligent aquaculture management, such as size estimation, counting and behavioral analysis of fish.

Sk Injamamul Islam, et al. [19] (2024) proposed the impact of diseases on aquaculture growth, fecundity, mortality rates, and marketability is profound. Hence, the ability to predict disease outbreaks is crucial to overcoming these challenges. Various infectious agents such as bacteria, viruses, fungi, and parasites can cause significant losses of fish in intensive aquaculture practices. In an aquaculture environment, the high host density coupled with restricted water flow promotes pathogen spread. Early detection of disease is crucial for farmers as mortality rates can reach as high as 100% if left untreated. Therefore, new techniques and technical solutions for disease management in aquaculture are required. In this context, data analytics technologies, such as internet of things (IoT) sensors, artificial intelligence, and machine learning, allow farmers to proactively monitor their farms and detect potential disease outbreaks before they strike.

Lim Leonard Whye Kit, et al. [20] (2024), they proposed the depletion of aquaculture lands and aquatic pollution are some of the major worrying predicaments challenging the future of this industry. Sustainable growth strategies are the only way out, and they must come hand in hand with the implementation of artificial intelligence to achieve the desired outcome high throughput in short time periods. The intelligent fish farm and smart cage aquaculture management system are some of the fruits of this drive, and the system keeps improving to date. In this review, we provide recent updates over the past half-decade of artificial intelligence implementation in fishery and aquaculture in hope to provide highlights and future directions to push the industry to greater heights.

Kavita Thakur, et al. [21] (2024), they proposed that the contrary, machine learning enabled models have shown tremendous potential in this regard, enabling rapid and accurate identification of communicable diseases. The objective of this research is to effectively identify as well as classify various communicable diseases using machine learning models in an efficient manner. The data of ten communicable diseases are considered, which are further analysed by pre-processing, feature selection, and visualization. Later machine learning models such as Random Forest, Gradient Boosting, Decision Tree, Adaptive Boosting, extreme Gradient Boosting, Extra Tree, Light Gradient Boosting Machine, and Categorical Boosting, along with the hybridization of XGBoost and Random Forest, are being applied, which are further evaluated using the parameters such as precision, false detection rate, recall, negative prediction value, F1 score, accuracy, and Matthew's correlation coefficient. The confusion matrix of all the models for various classes has also been generated to compute the values of performance metrics. During experimentation, it has been found that the random forest and hybridized model classifier obtained the highest accuracy of 99.9%, Random Forest, Extra Tree Classifier, CatBoost, and Hybrid classifier computed the highest Matthew's correlation coefficient score of 99.9%, the Gradient Boosting classifier obtained the best false detection rate value with 95.13% and negative predicted value with 189.82.

N Dahran, et. al [22] (2025), Proposed that the oxygen levels in aquaculture systems can induce hypoxia and hypercapnia, leading to physiological disruptions in fish. This study aimed to assess the effectiveness of dietary supplementation with camel whey protein hydrolysate in mitigating the effects

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of hypoxia stress on physiological limits in Oreochromis niloticus. In conclusion, dietary supplementation with shows promise in mitigating the detrimental events of hypoxia stress on fish growth, likely through its antioxidant activity and regulation of intestinal tight junction proteins, along with its anti-inflammatory potential and significantly enhances the activities of key digestive enzymes such as amylase, lipase, and trypsin.

A Vasumathi, et al. [23] (2024), they proposed that the conventional techniques for finding fish diseases, like visual inspection and microscopy, can be cumbersome and unreliable. The application of artificial intelligence for fish disease diagnosis has gained popularity in recent years. Based on fish photos or videos, artificial intelligence algorithms can be trained to recognize fish diseases. Fish disease detection could become quicker, more precise and easier to access as a result of this. Lack of extensive, top-notch datasets of fish photos and videos is one of the major obstacles to building AI models for fish disease identification. However, numerous research teams are attempting to solve this problem.

3. PROPOSED SYSTEM

Transfer learning is a machine learning technique that leverages knowledge gained from solving one problem to enhance learning in a different but related problem. This approach is particularly beneficial when there is a scarcity of data for the target task, as it allows models to utilize pre-existing knowledge from large, well-established datasets. By fine-tuning a pre- trained model on the new task, transfer learning can significantly improve performance and reduce the need for extensive data collection.

The flowchart illustrates the pipeline for an AI-powered fish disease classification system. It begins with collecting a fish disease dataset, followed by preprocessing and splitting it into training and testing sets. Features are extracted using the VGG19 model, and a Bagging- Random Forest classifier is applied for classification. The system outputs the fish disease type and evaluates performance. Additionally, the system accepts a test input image directly, extracts its features, classifies the disease, and provides suitable medicine suggestions accordingly.

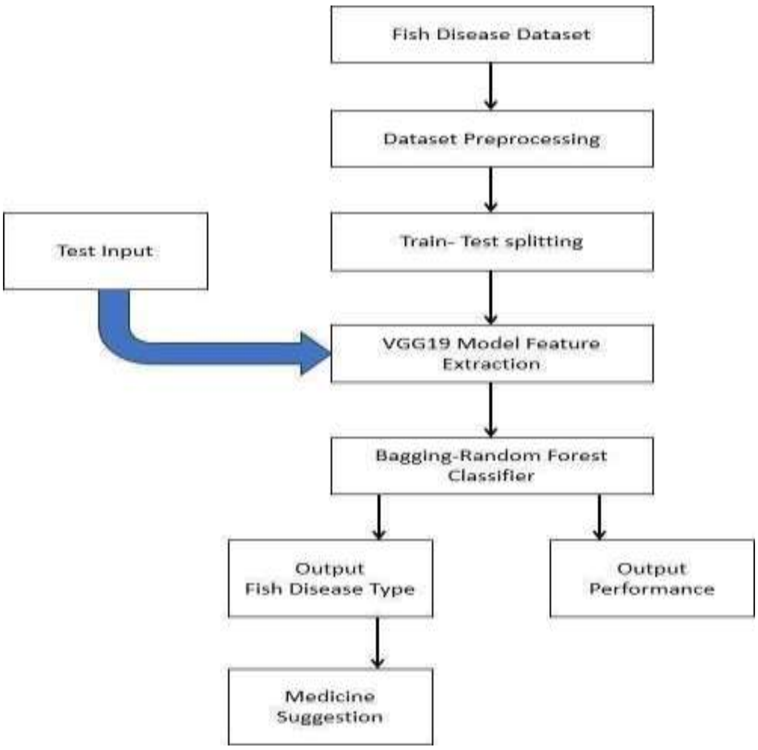

Fig 2: System Architecture

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Image preprocessing is a crucial step in fish disease classification, as it enhances image quality, removes noise, and standardizes data for better model performance. Raw images captured from underwater environments or fish farms often contain distortions, variations in lighting, and background noise, which can negatively impact classification accuracy. Preprocessing techniques help to mitigate these challenges, ensuring that the model focuses on relevant features rather than irrelevant variations.

One of the primary preprocessing techniques is image normalization, which adjusts pixel intensity values to a common scale. This step ensures that images have consistent brightness and contrast, making it easier for machine learning models to extract meaningful patterns. Another important step is image resizing, which standardizes input dimensions across all images. Fish images may come in different resolutions, and resizing them to a fixed size ensures uniformity in the dataset, reducing computational complexity and improving model efficiency.

VGG 19 CNN MODEL:

VGG19 is a convolutional neural network (CNN) architecture renowned for its simplicity and effectiveness in image classification tasks. Developed by the Visual Geometry Group at the University of Oxford, VGG19 consists of 19 layers: 16 convolutional layers and 3 fully connected layers. The architecture is characterized by its use of small 3×3 convolutional filters with a stride of 1 and padding to maintain spatial dimensions, combined with 2×2 max- pooling layers with a stride of 2 for downsampling. This design enables the network to capture hierarchical features, starting from simple edges and textures in the early layers to more complex patterns in the deeper layers.

In fish disease classification, VGG19's deep architecture allows it to effectively learn and extract intricate features from fish images, facilitating accurate detection and classification of various diseases. The model's depth and consistent use of small convolutional filters contribute to its robustness and effectiveness in handling complex image data, making it a valuable component in the system architecture for fish disease classification.

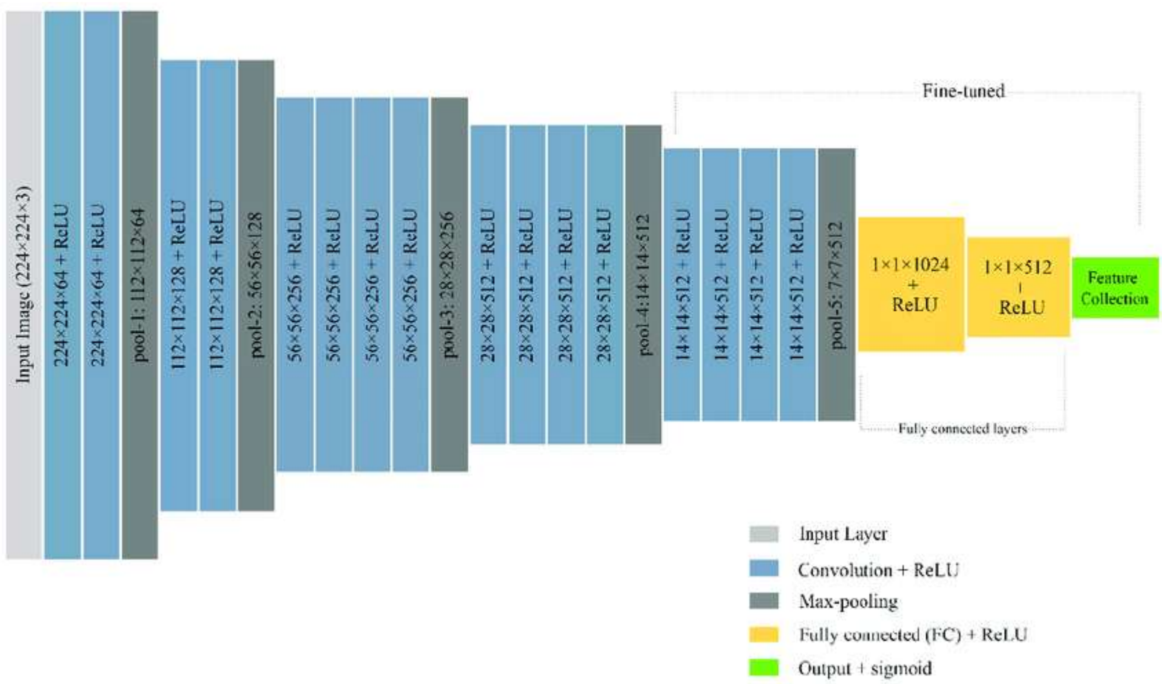

Fig. 3: VGG 19 CNN Model

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CONVOLUTION

The initial segment of VGG19 consists of 16 convolutional layers organized into five blocks. Each block typically contains two or three convolutional layers, each employing 3×3 filters with a stride of 1 and padding to maintain spatial dimensions. This configuration allows the network to capture hierarchical features, starting from simple edges and textures in the early layers to more complex patterns in the deeper layers. The consistent use of 3×3 filters throughout the network is a distinctive characteristic of VGG architectures, contributing to their effectiveness in image classification tasks.

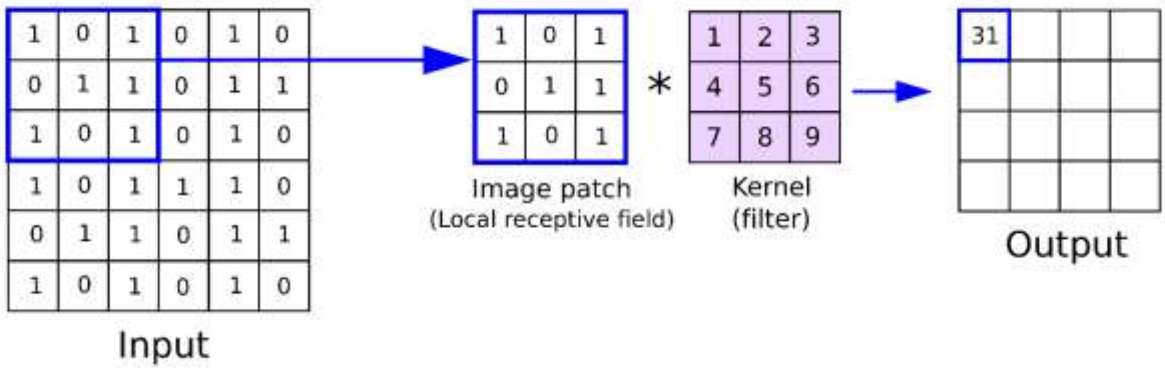

Fig. 4: Convolution Layer

RANDOM FOREST CLASSIFIER

The Random Forest classifier is a robust ensemble machine learning algorithm widely used in fish disease classification due to its high accuracy and resilience to overfitting. It operates by constructing multiple decision trees during training, each trained on a random subset of the data and features. In fish disease classification, the training dataset (X_train) comprises various features such as water quality parameters, fish health indicators, and environmental conditions, while the corresponding labels (Y_train) denote the presence or absence of specific diseases.

The dataset is partitioned into multiple sub-training sets (D1, D2, ..., Dk), each used to train individual decision trees (Decision Tree 1, Decision Tree 2, ..., Decision Tree k). Each tree independently analyzes the data and produces a classification result (Classification result 1, Classification result 2, ..., Classification result k). The Random Forest algorithm then aggregates these individual predictions through a majority voting mechanism to determine the final classification outcome. This ensemble approach enhances the model's generalization capability and accuracy.

In some implementations, techniques like gradient boosting are employed to further refine the voting decision, improving the model's performance. The final output features are derived from the collective decisions of all the decision trees in the forest, providing a comprehensive and reliable classification of fish diseases. This methodology has been effectively applied in various studies, demonstrating its efficacy in accurately identifying and categorizing fish diseases.

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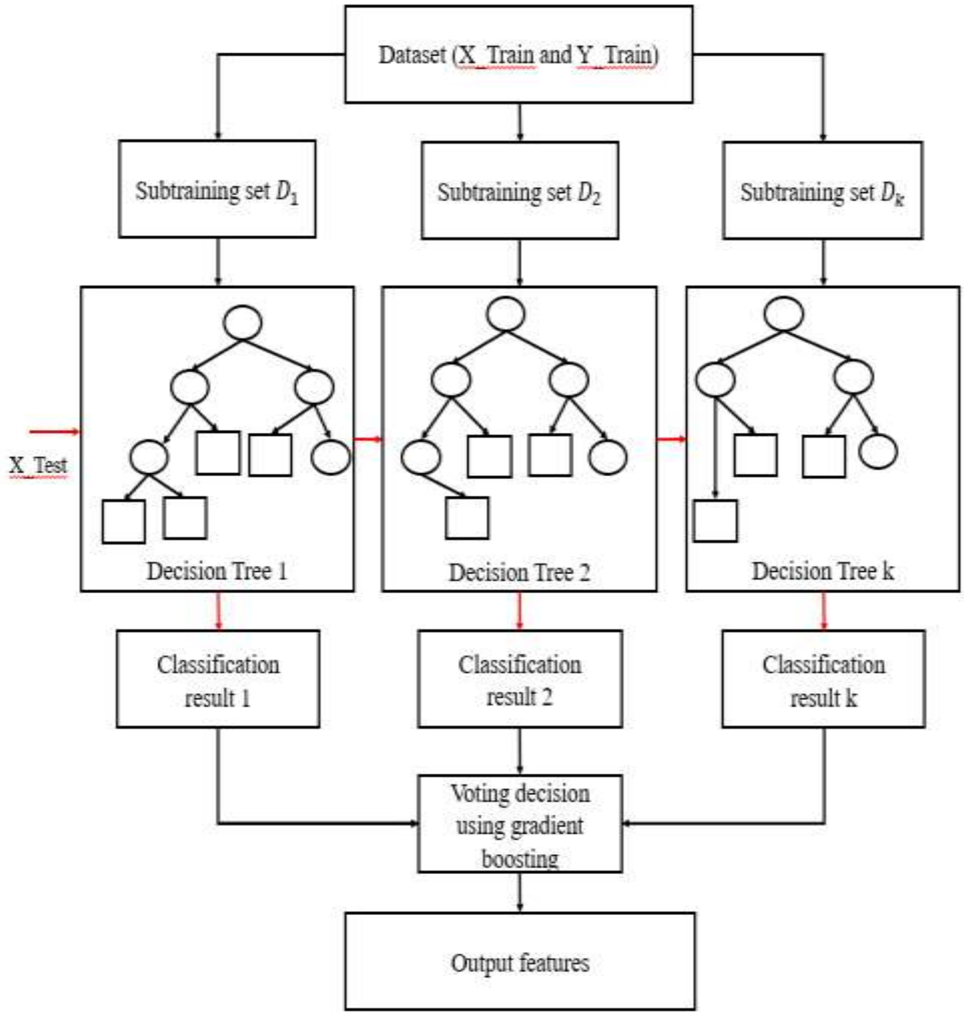

Fig. 5: Random Forest Classifier

ADVANTAGES OF VGG 19 AND RFC:

In fish disease classification, both VGG19 and Random Forest Classifier (RFC) offer distinct advantages:

VGG19 Advantages:

Deep Feature Extraction: VGG19's deep architecture enables it to capture intricate hierarchical features from fish images, facilitating accurate disease classification. Transfer Learning Capability: Pre-trained VGG19 models can be fine-tuned for specific tasks like fish disease classification, reducing the need for large labeled datasets. Simplicity and Uniformity: The straightforward design of VGG19, utilizing small 3x3 convolutional filters, simplifies implementation and understanding. High Performance: VGG19 has demonstrated strong performance in image classification tasks, achieving high accuracy rates in various applications. Availability and Support: VGG19 is widely available in popular machine learning libraries, making it accessible for implementation and experimentation.

Random Forest Classifier Advantages:

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High Accuracy: Random Forests are known for their high accuracy in classification tasks, effectively reducing overfitting and improving generalization. Robustness to Overfitting: The ensemble nature of Random Forests makes them less prone to overfitting compared to individual decision trees. Versatility: Random Forests can handle both classification and regression tasks and are capable of managing large datasets with higher dimensionality. Handling Missing Values: Random Forests can handle datasets with missing values, making them suitable for real-world data applications. Feature Importance: Random Forests provide insights into feature importance, aiding in feature selection and enhancing model performance.

4. RESULTS AND DISCUSSION

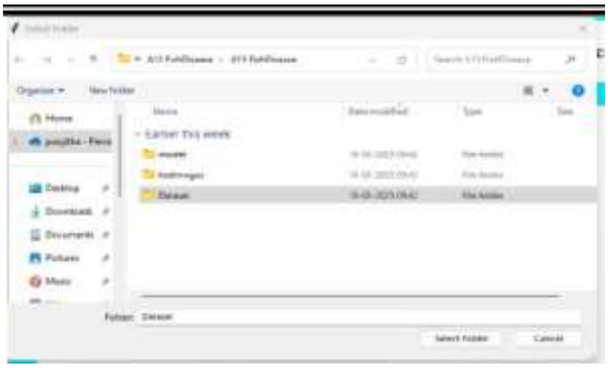

Fig. 6: Dataset Uploading

From this figure 6 shows the "Upload Dataset" functionality, where an admin user is selecting a dataset folder named "Dataset" from the system directory. This dataset will be used for training the AI model to classify fish diseases. Additional processing buttons like "VGG19 Feature Extraction," "Dataset Splitting," "Existing LRC," "Existing NBC," and "Proposed VGG19 with RFC" are visible, indicating different steps in the model training process.

Fig. 7: VGG19 Feature Extraction

From this figure 7 shows that the system has completed the feature extraction step using the VGG19 deep learning model. A message confirms "Image Preprocessing Completed," and "VGG19 Feature Extraction completed." The extracted features have dimensions of (1441, 10, 10, 512), where 1441 represents the number of images, and 10x10x512 represents the feature matrix for each image.

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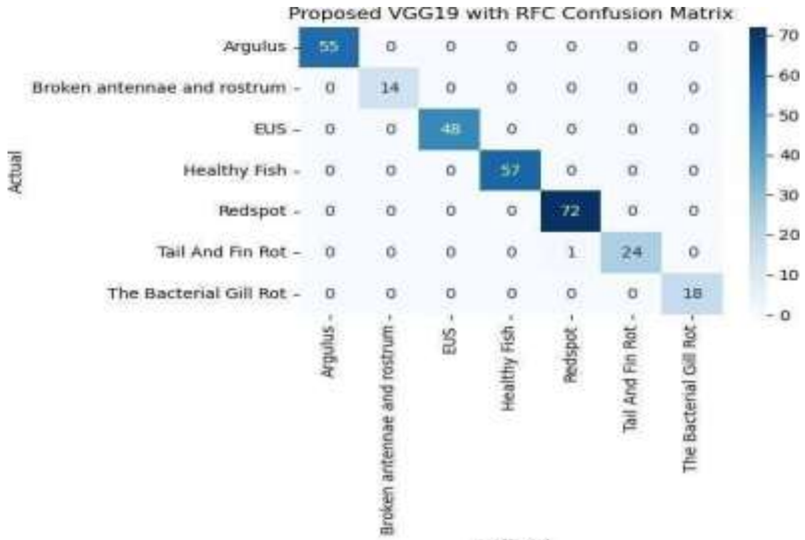

Fig. 8: Proposed VGG19 with RFC Confusion Matrix.

From this figure 8 shows the performance of the proposed VGG19 with Random Forest Classifier (RFC) model. The system achieved perfect scores, with 100% accuracy, precision, recall, and F1-score across all classes. The confusion matrix confirms that all instances were correctly classified without any misclassification. This demonstrates the superior effectiveness of the proposed model in fish disease classification.

(a) Argulus

(b) Broken Antennae and Rostrum

(c) Healthy Fish

(d) Redspot

Fig. 9: Output images

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(a) Argulus: This image shows a close-up of a fish's scales.There is a visible parasite attached to the fish.The parasite appears as a small, somewhat transparent creature.This is likely an Argulus, also known as a fish louse. Image highlights a parasitic infestation on the fish's body.

(b) Broken antennae and rostrum: This is a close-up shot of a fish's head. The fish's antennae appear to be damaged or broken. The rostrum, which is a snout-like projection, also shows signs of damage. The image focuses on the specific deformities on the fish's face. It highlights potential physical trauma or abnormalities in this area.

(c) Healthy fish: This image depicts a fish that appears to be in good health. The fish's body shows no obvious signs of disease or injury. Its fins are intact, and its scales look normal. This serves as a visual contrast to the other images showing diseased or damaged fish. It represents the baseline of a fish in a healthy state.

(d) Redspot: The photo presents a fish with a noticeable red spot on its body. This red spot is a key feature, suggesting a possible infection or injury. The surrounding area may also show subtle discoloration. The image draws attention to this localized abnormality. It indicates a potential health concern that needs further examination.

Table 1 Performance Comparison Table

Model	Accuracy	Precision	Recall	F1 Score
Existing LRC	0.7751	0.7750	0.7751	0.7720
Existing NBC	0.7405	0.7463	0.7405	0.7398
Proposed VGG19 With RFC	1.0000	1.0000	1.0000	1.0000

The table 1 performance comparison table presented in table 9.2, where LRC, NBC, and the proposed VGG19 with RFC was compared. LRC achieved 77.51% accuracy, showing balanced metrics but struggled with "Broken Antennae and Rostrum" and "Argulus." NBC had a slightly lower accuracy of 74.05%, excelling in "Broken Antennae and Rostrum" but underperforming in other categories. The VGG19 with RFC model achieved a perfect 100% accuracy, excelling in all metrics, highlighting its superior ability to capture complex patterns for fish disease classification.

5. CONCLUSION

The project introduces an AI-powered automatic fish disease classification and medicine suggestion system, integrating deep learning and machine learning techniques to enhance smart aquaculture. Leveraging VGG19-based feature extraction, the system generates meaningful representations from fish images and employs multiple classifiers, including Logistic Regression (LRC), Naïve Bayes (NBC), and Random Forest Classifier (RFC), to accurately classify various fish diseases. The incorporation of RFC with AME loss optimization significantly improves prediction accuracy while reducing misclassification errors. Designed with a user-friendly GUI built using Tkinter, the system enables both administrators and end- users to efficiently manage datasets, train models, and perform real-time disease classification. Administrative functionalities include dataset processing, feature extraction, and model training, whereas user functionalities facilitate instant image classification and medicine recommendations. Additionally, the system evaluates performance using key metrics such as accuracy, precision, recall, and F1-score while visualizing results through confusion matrices for better interpretability. By automating disease detection and treatment suggestions, this system minimizes reliance on expert fish pathologists, enabling early disease identification and preventive actions in

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aquaculture. Ultimately, it helps in reducing economic losses, improving fish health, and promoting sustainable fish farming practices, making it a valuable tool for modern aquaculture management.

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