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Development of a Convolutional Neural Network Model for Automated Ripeness Classification of Palm Oil Fresh Fruit Bunches

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Abstract:- The palm oil industry relies heavily on accurate ripeness classification of fresh fruit bunches (FFB) to optimize oil quality and production efficiency. Traditional ripeness assessment, often performed manually, is subjective, labor-intensive, and inconsistent, leading to suboptimal harvest decisions. This study aims to develop an artificial intelligence (AI)-based system that automates FFB ripeness classification using machine learning and computer vision techniques. The objective is to create a model that reliably classifies ripeness stages, thereby improving the consistency, efficiency, and accuracy of FFB assessments in real-time. This research introduces a novel approach by employing deep learning, specifically convolutional neural networks (CNNs), to recognize complex visual patterns in FFB images that correspond to various ripeness levels. Unlike conventional methods that rely on thresholding or simple color-based analysis, our approach leverages advanced image processing capabilities to enhance classification accuracy across diverse environmental conditions. The model was trained on a comprehensive dataset of FFB images, captured under different lighting conditions, to ensure adaptability and generalizability in real-world applications. Additionally, the model is designed for use on mobile devices, facilitating real-time, on-field classification accessible to workers in the palm oil industry.

Keywords:- *Convolutional Neural Networks, Fresh Fruit Bunch, Palm Oil Industry.*

I. INTRODUCTION

The palm oil industry is a vital sector globally, with palm oil used extensively across food, cosmetics, pharmaceuticals, and biofuels. As a high-yielding and efficient oil source, palm oil production plays a crucial role in meeting global vegetable oil demands. However, sustainable and efficient production practices are imperative, given the environmental impact of palm oil cultivation. A key aspect of enhancing both productivity and sustainability is the accurate determination of fresh fruit bunch (FFB) ripeness, as it directly influences the oil quality and quantity extracted. Ripeness classification is thus essential to optimize harvest timing, reduce waste, and ensure the highest possible quality of oil extracted from palm fruits[1].

Traditionally, the assessment of FFB ripeness has been performed manually, relying on visual inspection by skilled workers. This conventional approach often categorizes FFB based on external characteristics, such as color and texture, which correlate with internal oil content and quality. However, this manual classification is inherently subjective, susceptible to inconsistencies, and limited by environmental conditions like lighting. Human error, variations in training, fatigue, and subjective judgment all contribute to variations in the quality of classification, potentially leading to both economic losses and resource wastage. Additionally, manual inspection is time-consuming, impacting operational efficiency and limiting the scalability of accurate ripeness assessment in large plantations[2].

Fig 1: Oil Palms Fruits Bunch Piles

Recent advancements in artificial intelligence (AI) and machine learning offer transformative solutions for the agriculture industry, particularly in quality control and automation. AI-based approaches to classification can analyze complex patterns in images with higher accuracy and consistency than human inspectors, making them highly applicable to FFB ripeness classification. In this study, we explore the development of an AI-based classification system designed to identify FFB ripeness stages, enabling more reliable, efficient, and scalable assessment processes. This system leverages deep learning models, specifically convolutional neural networks (CNNs), trained on extensive image datasets to capture unique visual features associated with different ripeness stages. By integrating AI with image processing techniques, the model can detect subtle differences in color, texture, and form that indicate ripeness levels, offering a comprehensive solution for automated FFB classification[3]-[4].

A. The Need for Automated Ripeness Classification in the Palm Oil Industry

The palm oil industry faces numerous challenges that stem from inaccuracies in ripeness classification. Accurate ripeness determination directly impacts the oil extraction rate (OER), a critical metric for optimizing yield. Harvesting FFB too early or too late can result in lower oil yields, increased free fatty acids (FFA), and degraded oil quality, which affects both profitability and market competitiveness. Inaccurate ripeness classification can also lead to unnecessary harvesting of unripe or overripe bunches, contributing to waste and environmental degradation due to the resources expended in processing suboptimal fruit[5]-[6].

Automating the ripeness classification process has several potential benefits. First, automation can significantly improve classification accuracy, ensuring that only optimally ripe FFB are harvested. This can enhance yield quality and consistency, benefitting both producers and consumers. Second, automated classification can reduce reliance on manual labor, mitigating the risks associated with human error and improving operational efficiency. Third, automation can provide real-time classification, allowing workers to make on-the-spot decisions and adapt harvest strategies as needed, ultimately enhancing the flexibility and responsiveness of operations in the field[7]-[8].

B. The Role of AI and Machine Learning in FFB Classification

AI and machine learning have gained traction in agriculture for their ability to perform complex analyses on vast datasets, recognizing patterns that may be indiscernible to human observers. In recent years, these technologies have been applied to areas such as pest detection, crop monitoring, yield prediction, and quality assessment. For FFB ripeness classification, deep learning—a subset of machine learning—offers particular promise. CNNs, a type of deep learning model specifically suited to image analysis tasks, have demonstrated high accuracy in object recognition and classification tasks. CNNs are capable of learning spatial hierarchies of features from input images, which is critical for analyzing the intricate color and texture patterns indicative of FFB ripeness[9]-[10].

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The deep learning approach to FFB classification involves training a CNN model on a labeled dataset of FFB images, with each image associated with a specific ripeness level. The model learns to identify patterns associated with each ripeness stage by adjusting internal parameters during training. Once trained, the CNN model can process new images of FFB and classify them into ripeness categories with high accuracy. This approach leverages large amounts of image data to develop a model that is both robust to environmental variations (e.g., lighting and background conditions) and capable of real-time classification in the field[11].

Numerous studies have explored automated ripeness classification systems, with approaches ranging from traditional image processing techniques to advanced machine learning methods. Early methods focused on color analysis and simple thresholding techniques, where FFB images were segmented based on color intensity to distinguish ripe from unripe bunches. While effective to some extent, these methods lacked the flexibility to handle variations in lighting and background conditions, limiting their practical applicability[12]-[13].

More recent studies have incorporated machine learning models, including decision trees, support vector machines (SVM), and neural networks, to enhance classification accuracy. For instance, color and texture features extracted from FFB images have been used to train SVM classifiers, achieving moderate success in controlled settings. However, these models often struggle with complex real-world conditions, where variations in image quality, fruit appearance, and environmental factors can affect performance[14].

The advent of deep learning has introduced new possibilities for FFB ripeness classification. CNNs, with their ability to learn feature hierarchies automatically, represent a significant advancement over manual feature extraction approaches. Studies applying CNNs to agricultural image classification tasks have reported high accuracy rates, indicating the potential of this method for FFB classification. However, despite promising results, few studies have explored CNN-based models specifically tailored for FFB ripeness classification in diverse environmental conditions, particularly those that enable real-time deployment on mobile devices[15].

II. PROPOSED TECHNIQUE

A. Novelty and Contributions of this Study

This study presents a novel CNN-based model specifically designed for FFB ripeness classification, trained on a comprehensive dataset of FFB images captured under varying lighting and environmental conditions. Our model is unique in several ways:

- **Real-World Dataset**: We use a diverse dataset with images taken in field conditions to ensure the model's robustness across various scenarios, making it more adaptable to real-world applications.
- **Deep Learning Architecture**: Unlike traditional models that rely on handcrafted features, our model leverages CNNs to automatically learn complex features indicative of FFB ripeness. This end-to-end deep learning approach significantly improves classification accuracy and consistency.
- **Mobile Deployment**: We designed the model for compatibility with mobile devices, enabling on-site, real-time classification that workers can easily use. This integration of AI in mobile technology enhances practical applicability, bridging the gap between laboratory research and field deployment.
- **Scalability and Efficiency**: By automating ripeness classification, our approach improves operational scalability and reduces the time and labor costs associated with manual assessment.

B. CNN Working Principle for FFB Classification

CNNs operate by automatically learning and combining spatial hierarchies of visual features from FFB images to classify ripeness stages. Convolutional layers capture basic to advanced image features, activation functions introduce non-linearity, pooling layers reduce dimensionality and enhance robustness, and fully connected layers integrate all extracted information for final classification. The CNN is trained through backpropagation, with iterative optimization refining the model’s accuracy. By leveraging these principles, CNNs enable a scalable, efficient, and robust solution for ripeness classification in the palm oil industry, transforming quality control processes and enhancing productivity in real-world conditions.

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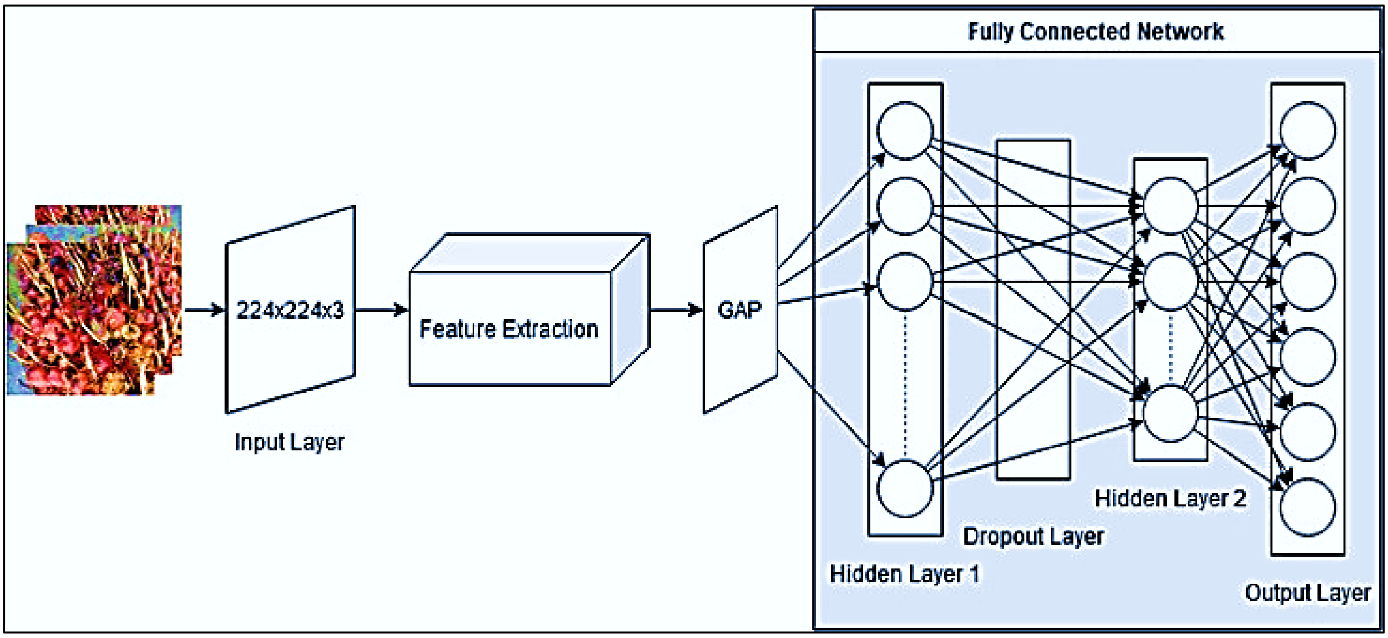

Fig 2: Schematic Diagram of Proposed Technique

Convolutional Neural Networks (CNNs) are a class of deep learning models particularly well-suited for image recognition tasks due to their ability to learn spatial hierarchies and patterns directly from pixel data. In this study, CNNs are employed to analyze images of fresh fruit bunches (FFB) and automatically classify their ripeness based on visual features indicative of different maturity stages.

➢ *Stage 1: Convolutional Layers and Feature Extraction*

- **Convolution Operations:** At the core of CNNs are convolutional layers, where small filters or kernels are applied across the image to detect low-level features such as edges, colors, and textures. These kernels slide over the image, performing element-wise multiplications and summing the results to produce a feature map. In the context of FFB ripeness classification, the convolutional layers initially capture basic visual cues like color gradients and textures that may correspond to different ripeness stages.
- **Hierarchical Feature Learning**: As the input image passes through successive convolutional layers, CNNs learn increasingly complex and abstract patterns. Early layers detect basic features, while deeper layers capture higher-level patterns specific to FFB ripeness, such as the characteristic texture, shape, and color variations at different maturity levels.

➢ *Stage 2: Activation Functions and Non-Linearity*

- **ReLU Activation**: After each convolution operation, the Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity into the model. This enables CNNs to capture more complex relationships between pixels. The ReLU function sets negative values to zero, preserving only the positive feature values, which improves learning speed and makes the model more robust to variations in image conditions.
- **Non-linear Decision Boundaries**: By incorporating non-linearity, CNNs can model non-linear decision boundaries required to classify the various ripeness stages accurately, as ripeness involves subtle and complex changes in fruit appearance that cannot be captured by linear transformations alone.

➢ *Stage 3: Pooling Layers for Dimensionality Reduction*

- **Max Pooling**: Pooling layers reduce the spatial dimensions of the feature maps, making the model more computationally efficient and robust to minor variations in the input image, such as slight rotations or lighting changes. Max pooling, where the maximum value within a filter region is retained, is commonly used. This approach helps the model focus on the most prominent features in each local region, which is essential for differentiating ripeness stages.
- **Spatial Invariance**: Pooling layers help the model become invariant to small translations and distortions, which is particularly useful in field conditions where FFB images might vary due to environmental factors. This invariance ensures that the model generalizes well across different images.

➢ *Stage 4: Fully Connected Layers and Classification*

- **Flattening and Dense Layers**: After feature extraction through convolutional and pooling layers, the high-level features are flattened into a one-dimensional vector and passed through fully connected (dense) layers. These layers combine all extracted features to form the final ripeness classification decision. Each neuron in the dense layer is connected to every neuron in the previous layer, allowing the model to integrate information from all parts of the image.

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- **Softmax for Multi-Class Classification**: In this study, the fully connected layers culminate in a softmax activation function, particularly if multiple ripeness stages (classes) are present. The softmax function generates a probability distribution across all ripeness classes, assigning a probability score to each stage. The class with the highest probability is chosen as the predicted ripeness stage, providing a straightforward and interpretable classification result.

➢ *Stage 5: Training the CNN with Supervised Learning*

- **Backpropagation and Gradient Descent**: During training, the CNN learns to minimize the difference between its predictions and the actual labels (ground truth) by adjusting its weights through backpropagation and gradient descent. For FFB ripeness classification, each image is labeled according to its ripeness stage, and the model iteratively updates its parameters to improve classification accuracy.
- **Loss Function**: A categorical cross-entropy loss function is typically used in multi-class classification tasks like FFB ripeness classification. This function quantifies the error between the predicted probabilities and the actual labels, guiding the model to correct its predictions over successive training epochs.

➢ *Stage 6: Transfer Learning for Improved Performance*

- **Pre-trained Models**: Transfer learning, which uses pre-trained CNN models on large datasets, may also be applied in FFB classification to leverage previously learned features. By fine-tuning a pre-trained model on the FFB dataset, the model can benefit from general image features learned previously, such as shape and texture detection, improving both training speed and accuracy, especially if the dataset is limited in size.

➢ *Stage 7: Real-Time Classification and Field Deployment*

- **Model Optimization for Mobile Devices**: After training, the model is optimized for deployment on mobile devices, allowing field workers to perform real-time ripeness classification. Techniques like model compression and quantization may be applied to reduce computational requirements, ensuring that the CNN operates efficiently on portable devices without compromising accuracy.

C. Mathematical Model

To mathematically model a Convolutional Neural Network (CNN) for FFB ripeness classification, the core mathematical components involved, including the convolution operation, activation functions, pooling layers, fully connected layers, and the loss function used during training.

➢ *Convolution Operation*

The convolution operation is central to feature extraction in CNNs. Mathematically, the convolution of an input image I with a kernel (or filter) K is defined as:

$$I * K\ (X, Y) = \sum_{i=-a}^{a} 1 \sum_{j=-b}^{b} (X + i, Y + j) * K(i, j) \qquad (1)$$

Where,
I(x,y) is the pixel value at location (x,y) in the input image,
K(i,j) is the filter kernel with dimensions (2a+1,2b+1),
(I∗K)(x,y) is the resulting feature map

Each convolution layer applies multiple filters to the input, producing a set of feature maps. If the image size is M×N and the kernel size is f×f the resulting feature map size (with stride s and padding p) is given by:

$$Output\ Dimension = \frac{M-f+2p}{S} + 1 \qquad (2)$$

➢ *Activation Function*

The Rectified Linear Unit (ReLU) is commonly used to introduce non-linearity. Mathematically, ReLU is defined as:

$$ReLU(x) = max(0, x) \qquad (3)$$

For each element x in the feature map, ReLU keeps all positive values the same and sets all negative values to zero.

➢ *Pooling Layer*

Pooling reduces the spatial dimensions of the feature map, preserving essential features while decreasing computational requirements. Max pooling is typically used and is mathematically represented as:

$$P(x, y) = max\{F(i, j) \mid (i, j) \in R(x, y)\} \qquad (4)$$

Where
F(i,j) is the input feature map,
R(x,y) represents a small window
P(x,y) is the output of the pooling layer.
Pooling reduces the feature map dimensions by a factor defined by the pool size.

➢ *Fully Connected Layer*

After feature extraction through convolution and pooling, the CNN moves to fully connected layers to perform the classification. The output of the convolution and pooling layers is flattened into a one-dimensional vector x\mathbf{x}x and passed to a fully connected layer, where each neuron computes a weighted sum:

$$y = wTx + b \qquad (5)$$

Where:

- x is the input vector from the previous layer,
- w represents the weight vector for the neuron,
- b is the bias term,
- y is the neuron's output, which is then passed through an activation function

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➢ ***SoftMax for Classification***

In the final layer, a softmax function is applied to convert the output scores into probabilities for each ripeness class. For CCC classes, the softmax function for the i-th class is:

$$softmax(zi) = \frac{e^{zi}}{\sum_{J=1}^{C} e^{zj}} \quad (6)$$

Where zi represents the raw score (logit) output for class i. Softmax ensures that the sum of probabilities across all classes equals 1, allowing for multi-class classification.

D. Advantages

The use of a Convolutional Neural Network (CNN) model for automated ripeness classification of palm oil fresh fruit bunches (FFB) offers several advantages, particularly in the context of agricultural quality control and production efficiency.

➢ *Improved Accuracy and Consistency*

- **Reduced Subjectivity**: CNNs provide a consistent, objective classification by eliminating human judgment variations. This ensures reliable ripeness classification, which is crucial for optimizing harvest quality.
- **High Accuracy**: CNNs excel in image recognition, allowing them to detect subtle visual differences in FFB ripeness that may be challenging for human inspectors. This increases accuracy in classification and improves yield quality.

➢ *Increased Efficiency and Reduced Labor Costs*

- **Time Savings**: Automated classification is faster than manual inspection, enabling high throughput and reducing the time required for ripeness assessment in large plantations.
- **Labor Reduction:** By automating ripeness detection, the need for skilled labor is minimized, helping address labor shortages and reduce operational costs associated with manual assessments.

➢ *Real-Time, On-Field Classification*

- **Mobile Compatibility:** With CNN models optimized for mobile deployment, classification can be performed on-site using mobile devices, allowing for immediate decisions and adjustments in harvesting schedules.
- **Adaptability to Field Conditions**: CNNs can be trained to account for environmental variations such as lighting changes, enabling robust classification directly in field conditions.

➢ *Enhanced Yield and Quality Control*

- **Optimized Harvest Timing**: By accurately assessing ripeness, producers can ensure FFB is harvested at the optimal stage, maximizing oil yield and quality.
- **Reduced Waste**: Correct ripeness classification prevents harvesting under- or overripe fruits, reducing waste and ensuring resource-efficient operations.

E. Applications

CNN-based ripeness classification can benefit various stages of palm oil production, from field operations to processing, supply chain management, and quality control. It has the potential to revolutionize the industry by enhancing productivity, reducing waste, and supporting sustainable practices, making it a valuable tool for modernizing agricultural practices and improving overall production efficiency.

➢ *Automated Ripeness Classification in Palm Oil Plantations*

- Harvest Optimization: CNN-based ripeness detection can be deployed directly on-site in plantations to assist workers in identifying optimally ripe FFB, improving harvest timing and oil quality.
- Yield Maximization: Accurate ripeness assessment enables more efficient production, ensuring that FFBs with the highest oil yield are harvested at their peak.
- Quality Control: Automated ripeness classification ensures consistency in the quality of harvested FFB, which is essential for producing high-grade palm oil.

➢ *Mobile and On-Field Ripeness Detection Tools*

- Mobile Application for Workers: With a CNN model deployed on mobile devices, workers can classify FFB ripeness in real-time, reducing decision-making time and improving operational efficiency.
- Portable Devices for Remote Areas: In regions where internet access may be limited, a CNN-based application can be embedded into portable devices that do not require internet connectivity, enabling seamless use in remote locations.

➢ *Automated Sorting Systems in Processing Plants*

- Quality Sorting: Processing plants can use CNNs to automate the sorting of FFB based on ripeness levels, ensuring that only optimally ripe bunches are processed, thus improving overall product quality.
- Waste Reduction: By sorting out underripe or overripe FFB, automated systems help reduce waste in the production line, making operations more resource-efficient and sustainable.

➢ *Precision Agriculture and Smart Farming*

- Data Collection and Analysis: In precision agriculture, CNN-based ripeness classification can collect data on ripeness stages, providing insights that can guide future planting and harvesting practices.

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- Integration with IoT: The CNN model can be integrated with IoT devices for automated data gathering, enabling smart farming systems to optimize ripeness detection and harvesting remotely.

III. CONCLUSION

The application of AI, specifically CNNs, to FFB ripeness classification marks a promising advancement for the palm oil industry, offering a robust, efficient, and scalable solution for quality control. This study contributes a novel, real-time classification system tailored for field deployment, bridging the gap between AI research and practical application. By improving ripeness assessment accuracy, our approach not only enhances palm oil quality but also promotes sustainable production practices, aligning with industry goals to meet growing global demand responsibly.

REFERENCES

[1]. W. Aji and K. Hawari, "A study of deep learning method opportunity on palm oil FFB (fresh fruit bunch) grading methods," in *2019 Ahmad Dahlan International Conference Series on Engineering and Science (ADICS-ES 2019)*, Atlantis Press, 2019, pp. 22–25. Accessed: Nov. 12, 2024. [Online]. Available: https://www.atlantis-press.com/proceedings/adics-es-19/125924425

[2]. R. Rahutomo *et al.*, "AI-based ripeness grading for oil palm fresh fruit bunch in smart crane grabber," in *IOP Conference Series: Earth and Environmental Science*, IOP Publishing, 2020, p. 012147. Accessed: Nov. 12, 2024. [Online]. Available: https://iopscience.iop.org/article/10.1088/1755-1315/426/1/012147/meta

[3]. S. Zolfagharnassab, A. R. B. M. Shariff, R. Ehsani, H. Z. Jaafar, and I. B. Aris, "Classification of oil palm fresh fruit bunches based on their maturity using thermal imaging technique," *Agriculture*, vol. 12, no. 11, p. 1779, 2022.

[4]. C. P. Prasad and N. Nireekshan, "A Higher Voltage Multilevel Inverter with Reduced Switches for Industrial Drive," *Int. J. Sci. Eng. Technol. Res. IJSETR*, vol. 5, no. 1, 2016, Accessed: Nov. 12, 2024. [Online]. Available: https://methodist.edu.in/web/uploads/naac/2019-11-19%2012_24_22pm%2092.pdf

[5]. A. Septiarini, H. R. Hatta, H. Hamdani, A. Oktavia, A. A. Kasim, and S. Suyanto, "Maturity grading of oil palm fresh fruit bunches based on a machine learning approach," in *2020 Fifth International Conference on Informatics and Computing (ICIC)*, IEEE, 2020, pp. 1–4. Accessed: Nov. 12, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9288603/

[6]. N. Nireekshana, N. Ravi, and K. R. Kumar, "A Modern Distribution Power Flow Controller With A PID-Fuzzy Approach: Improves The Power Quality," *Int. J. Electr. Electron. Res.*, vol. 12, no. 1, pp. 167–171, 2024.

[7]. J. Y. Goh, Y. Md Yunos, and M. S. Mohamed Ali, "Fresh Fruit Bunch Ripeness Classification Methods: A Review," *Food Bioprocess Technol.*, Jun. 2024, doi: 10.1007/s11947-024-03483-0.

[8]. N. Nireekshana, R. R. Chandran, and G. V. Narayana, "Frequency Regulation in Two Area System with PSO Driven PID Technique," *J Power Electron Power Syst*, vol. 12, no. 2, pp. 8–20, 2022.

[9]. N. Nireekshana, R. Ramachandran, and G. V. Narayana, "A New Soft Computing Fuzzy Logic Frequency Regulation Scheme for Two Area Hybrid Power Systems," *Int. J. Electr. Electron. Res.*, vol. 11, no. 3, pp. 705–710, Aug. 2023, doi: 10.37391/IJEER.110310.

[10]. N. Nireekshana, R. Ramachandran, and G. Narayana, "A Novel Swarm Approach for Regulating Load Frequency in Two-Area Energy Systems," *Int J Electr Electron Res*, vol. 11, pp. 371–377, 2023.

[11]. N. Nireekshana, R. Ramachandran, and G. V. Narayana, "A Peer Survey on Load Frequency Contol in Isolated Power System with Novel Topologies," *Int J Eng Adv Technol IJEAT*, vol. 11, no. 1, pp. 82–88, 2021.

[12]. J. W. Lai, H. R. Ramli, L. I. Ismail, and W. Z. Wan Hasan, "Oil palm fresh fruit bunch ripeness detection methods: A systematic review," *Agriculture*, vol. 13, no. 1, p. 156, 2023.

[13]. N. Nireekshana, T. H. Nerlekar, N. Kumar, and M. Mohsin, "An Innovative Solar Based Robotic Floor Cleaner," *Int. J. Innov. Sci. Res. Technol. IJISRT*, vol. 8, no. 4, pp. 1880–1885, 2023.

[14]. N. Fadilah, J. M. Saleh, H. Ibrahim, and Z. A. Halim, "Oil palm fresh fruit bunch ripeness classification using artificial neural network," in *2012 4th International Conference on Intelligent and Advanced Systems (ICIAS2012)*, IEEE, 2012, pp. 18–21. Accessed: Nov. 12, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/6306151/

[15]. N. Khan, M. A. Kamaruddin, U. U. Sheikh, Y. Yusup, and M. P. Bakht, "Oil palm and machine learning: Reviewing one decade of ideas, innovations, applications, and gaps," *Agriculture*, vol. 11, no. 9, p. 832, 2021.