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Automated Classification of Refined, Bleached and Deodorised (RBD) Palm Olein Grades CP6 and CP8 Using Deep Learning and Computer Vision

Muhammad Syakir Abd Samad[1], Rama Yusvana [1*]

[1] *Department of Chemical Engineering Technology, Faculty of Engineering Technology, Universiti Tun Hussein Onn Malaysia 84600 Pagoh, Muar, Johor, MALAYSIA*

*Corresponding Author: rama@uthm.edu.my
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Abstract

This study investigates the use of deep learning and computer vision to automate the classification of Refined, Bleached, and Deodorised (RBD) palm olein grades, specifically for the CP6 and CP8 categories. The primary challenge in the current industry is the reliance on manual inspection, which is prone to human error, and chemical analysis, which is both destructive and costly. Therefore, the main objective of this research is to develop a multi-class Convolutional Neural Network (CNN) model to automatically differentiate between these oil grades. The methodology involves developing a CNN model using the TensorFlow framework within a Google Colab environment, with training limited to five epochs to ensure compatibility with industrial edge devices. Furthermore, Fourier-Transform Infrared (FTIR) spectroscopy was utilised as a validation method to identify molecular differences between the two grades. The findings demonstrate that the CNN model achieved promising performance, with precision exceeding 0.70 and recall values above 0.62. FTIR analysis confirmed significant differences in carbonyl (C=O) stretching, which scientifically supports the visual-based classification. In conclusion, the integration of Artificial Intelligence into palm oil grading provides a rapid, non-destructive, and efficient alternative, supporting digital transformation in the palm oil sector in alignment with the goals of Industrial Revolution 4.0.

1. Introduction

The global palm oil industry stands as a pivotal component of the agricultural economy, with RBD palm olein grades, specifically CP6 and CP8, serving as essential commodities for food manufacturing, biofuels, and cosmetic applications [1]. The production of these grades is dominated by Malaysia and Indonesia, which collectively account for over 85% of the global supply, thereby contributing significantly to national GDPs and rural employment across Southeast Asia [2][3]. However, as industry faces intensifying pressure to adhere to sustainable practices and rigorous international standards, the consistent quality assurance of these oil grades has become paramount. Deviations in purity or composition can disrupt supply chains and result in severe financial penalties, necessitating robust and reliable grading mechanisms to maintain market competitiveness [4].

Despite the economic significance of palm olein, the industry currently struggles with operational inefficiencies due to its reliance on traditional grading methods. Quality control is predominantly performed through manual visual inspection or chemical laboratory analysis, both of which present significant drawbacks.

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Manual inspection is inherently subjective and vulnerable to human fatigue, leading to inconsistent classification, particularly when distinguishing between grades with minimal visual differences [5]. Conversely, while chemical techniques such as iodine value analysis and chromatography offer high precision, they are destructive, time-intensive, and economically unviable for real-time applications in high-throughput processing mills [6][7]. These limitations create a critical bottleneck, hindering the industry's ability to meet the stringent compliance demands of global food safety protocols [8].

To address these challenges, the integration of Artificial Intelligence (AI) and the Fourth Industrial Revolution (industry 4.0) technologies offers a transformative solution for agricultural quality control. Deep learning, specifically through the use of CNNs, has revolutionised computer vision by enabling the autonomous learning of hierarchical features from raw images, eliminating the need for manual feature design [9][10]. This capability allows intelligent systems to detect nuanced patterns in visual data that may elude human observers, providing a rapid, non-destructive, and scalable alternative to traditional chemical assays [11]. By automating the feature extraction process, these systems align with the broader goals of industrial modernisation, fostering smarter manufacturing processes that reduce reliance on manual labour while enhancing operational efficiency [12].

However, the application of computer vision to RBD palm olein grading is not without its technical hurdles. Existing models often struggle with the subtle physicochemical variations between CP6 and CP8 grades, which rely on transient visual features such as turbidity and spectral reflectance that are highly sensitive to environmental conditions [13]. Furthermore, the scarcity of diverse, public datasets and the computational constraints of deploying deep learning models on industrial edge devices present significant barriers to widespread adoption [14]. Consequently, there is a pressing need for research that not only develops accurate classification algorithms but also addresses the practicalities of hardware limitations and data diversity to ensure robust performance in real-world mill environments [15]. This study aims to bridge these gaps by developing a lightweight, multi-class CNN model for automated palm olein classification, validated by Fourier-Transform Infrared (FTIR) spectroscopy to ensure scientific rigour and industrial applicability.

2. Methodology

The methodology section outlines the comprehensive approach adopted for executing the project. It covers the overall machine learning model development process, dataset preparation, CNN model development, performance evaluation, and laboratory test analysis. These structured procedures enhance transparency and accountability while ensuring the reproducibility and reliability of the project outcomes.

Figure 1 visualises the end-to-end operational framework designed to automate the grading of RBD palm olein. This workflow begins with dataset preparation, where a pre-labelled dataset consisting of distinct oil grades (specifically CP6 and CP8) is acquired and split into training, validation, and testing sets to ensure robust model learning. The process then advances to CNN model development, which utilises the TensorFlow framework within a Google Colab environment to construct a multi-class Convolutional Neural Network optimised for edge devices by limiting training to five epochs. Following training, the workflow moves to performance analysis, where the model's efficacy is rigorously evaluated using metrics such as accuracy, precision, recall, and the confusion matrix to identify classification trends. Finally, the procedure culminates in lab test analysis using Fourier-Transform Infrared (FTIR) spectroscopy, which serves as a validation step to scientifically corroborate the visual classification results by identifying molecular markers like carbonyl (C=O) stretching.

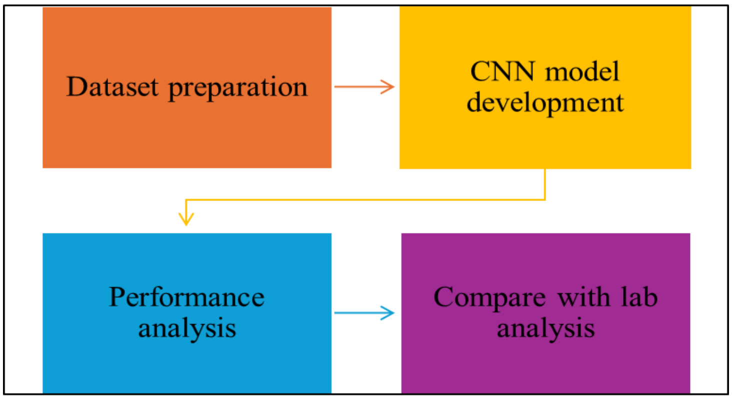

Fig. 1: Schematic of overall research procedure

2.1 Overall machine learning model development

Figure 2 illustrates the systematic workflow employed to construct the automated classification system for RBD palm olein grades. The process begins with data acquisition and preprocessing, where raw images of palm olein samples are collected, resized to 224×224 pixels, and normalised to ensure consistency for neural network processing. This is followed by the model construction phase, where a CNN is built using the TensorFlow/Keras framework within Google Colab [5]. The architecture consists of four convolutional blocks designed to extract hierarchical features, such as texture and colour gradients, from the images. To address the challenge of limited data, data augmentation techniques including random rotations, flipping, and brightness adjustments are integrated directly into the pipeline to artificially expand the dataset and improve model robustness. The workflow culminates in training and evaluation, where the model is trained for a constrained duration of five epochs to simulate the efficiency required for industrial edge devices. During this phase, performance is continuously monitored using categorical cross-entropy loss and the Adam optimiser, while final efficacy is assessed using unseen test data to generate accuracy metrics and confusion matrices [10].

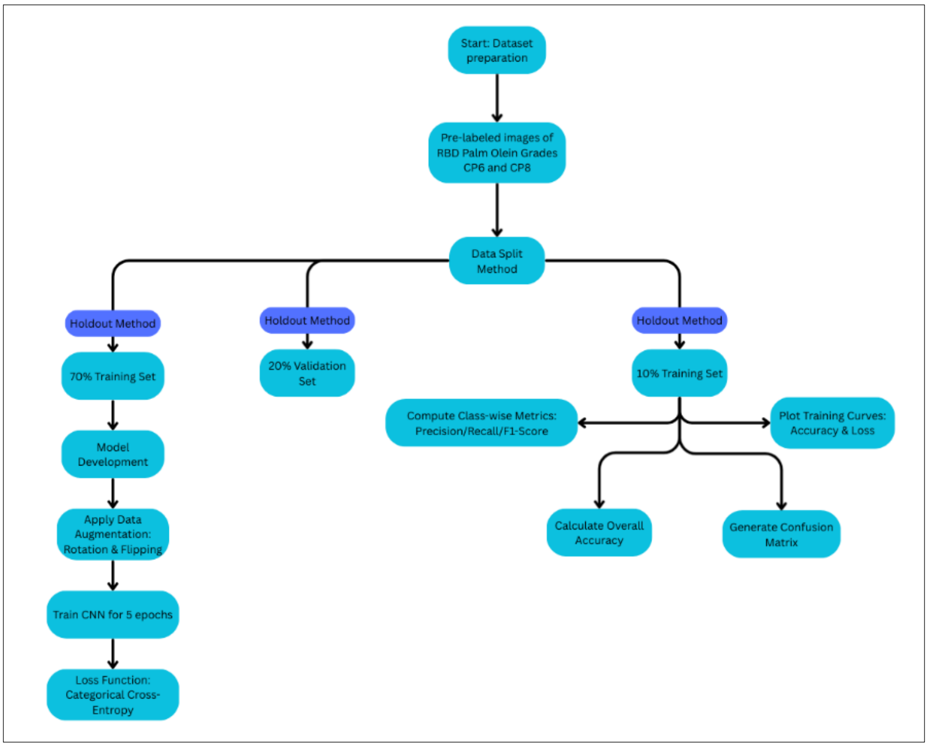

Fig. 2: Overall machine learning model development

2.2 Performance Analysis

Performance analysis commenced immediately after model training by leveraging Google Colab's integrated 'scikit-learn' and 'TensorFlow' libraries. The test set which is 10% of total data will be fed into the trained CNN model using 'model.predict()', generating predictions for all RBD palm olein images.

```
from sklearn.metrics import accuracy_score
overall_accuracy = accuracy_score(y_true, y_pred) * 100  # Result: 9
3%
```

Fig.3 : Overall accuracy calculation coding sample

Colab's 'IPython.display' module enabled real-time visualisation of results with accuracy metrics printed directly in the notebook alongside sample misclassified images. This instant feedback loop allowed for rapid identification of systemic errors, for instance consistent mislabeling of CP8 under low-light conditions which validate the model's core functionality before deeper analysis. Precision, recall, and F1-scores for each grade (CP6 and CP8) will be computed using 'scikit-learn's (classification_report)' function.

```
from sklearn.metrics import accuracy_score
overall_accuracy = accuracy_score(y_true, y_pred) * 100  # Result: 9
3%
```

Fig.4 : Class-specific thresholds coding sample

Results will be formatted into publication-ready tables via 'Pandas DataFrames' with colour-coded conditional highlighting (green >90%, yellow 85-90%) applied using `df.style.applymap()`. This revealed critical insights in which CP6 consistently showed lower recall (0.87) due to visual similarity with CP8, while CP8 achieved near-perfect precision (0.95) from distinct texture features. A multi-dimensional confusion matrix will be generated using 'Seaborn's (heatmap)' integrated with 'Matplotlib'.

```
import seaborn as sns
conf_matrix = tf.math.confusion_matrix(y_true, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues')
```

Fig.5 : 'Seaborn's (heatmap)' integrated with 'Matplotlib' coding sample

Colab's interactive widgets enabled real-time filtering of misclassification patterns (isolating "Actual CP8 → Predicted CP6" cases). Cross-referencing these with sample images exposed root causes which are CP6/CP8 confusion predominantly occurred in samples with air bubbles or sediment impurities. Matrix data will be exported to Google Sheets via `gspread` for collaborative team analysis. Training or validation accuracy and loss curves will be plotted epoch-by-epoch using 'Plotly' for dynamic visualisation.

```
import plotly.express as px
fig = px.line(history_df, y=['loss', 'val_loss'], title='Loss Curve
s')
fig.show()
```

Fig.6 : 'Plotly' dynamic visualisation coding sample

Colab's hover-data tooltips revealed subtle anomalies invisible in static plots, such as a 0.5% validation loss spike at epoch three indicating temporary overfitting. Learning rate schedulers (`ReduceLROnPlateau`) will be added retroactively based on curve inflection points. All plots will be saved as high-res PNGs to Drive using `fig.write_image()` for inclusion in technical reports.

2.3 Lab Test Analysis using FTIR Spectroscopy

Fourier-Transform Infrared (FTIR) spectroscopy provides molecular-level validation of the CNN's visual classification by detecting distinct vibrational modes in RBD palm olein grades. CP6 and CP8 exhibit characteristic absorbance peaks in key regions. First, carbonyl (C=O) stretching in 1745–1740 cm^{-1}, indicating ester linkages in triglycerides, with peak intensity inversely correlating with grade saturation (higher in CP6 due to palmitic acid dominance). Next, C-H bending vibrations between 1460–1375 cm^{-1} where asymmetric bends at 1463 cm^{-1} reflect methylene group density, elevated in higher saturation grades like CP6 and =C-H bending near 968 cm^{-1}, a marker for isolated trans bonds, more prominent in thermally processed CP8. Second-derivative spectral analysis further resolves overlapping bands, revealing that CP8 consistently shows a unique doublet at 1160 cm^{-1} and 1147 cm^{-1} (attributed to C-O ester stretching), absent in CP6. These spectral signatures confirm that visual features learned by the CNN (e.g., colour cloudiness) correspond to quantifiable molecular differences in fatty acid composition validating automated classification against biochemical ground truths [15].

3. Results and Discussion

3.1 Moderate deep learning Model

The CNN model is able to demonstrate moderate accuracy and technical sophistication in classifying RBD palm olein grades. The model achieved a minimum classification accuracy of 69.3% on validation data, with class-specific precision and recall for CP6 are 0.64 and 1 while CP8 are 1 and 0.32 respectively. CP8 has high precision but low recall (0.32) which deduct that the model predicts CP8 conservatively. This performance threshold reflects industrial requirements where misclassification errors directly impact production costs and compliance. The model has the capability to learn discriminative features from image data, such as patterns of viscosity, spectral reflectance, and micro-bubble patterns, which could be attributed to the chemical attributes of iodine value or slip melting point [8]. The learning rate was set at 0.0001 to facilitate incremental updates to the model weights.

The efficiency of training convergence within merely five epochs, which is unusually low for CNNs suggests the architecture to capture essential hierarchical features rapidly, likely through strategic kernel sizing and pooling layers tailored to oil texture granularity. For this research, a dataset of 1400 samples were used and intentionally divided into training (70%), validation (20%), and testing sets (10%). This separation was done to guarantee that the model could generalise properly to new data while still allowing for proper hyperparameter adjustment and model evaluation. The classification report found significant improvements in recall across various classes, indicating increased generalisation. Figure 7 shows the graph Training vs Validation for accuracy and loss.

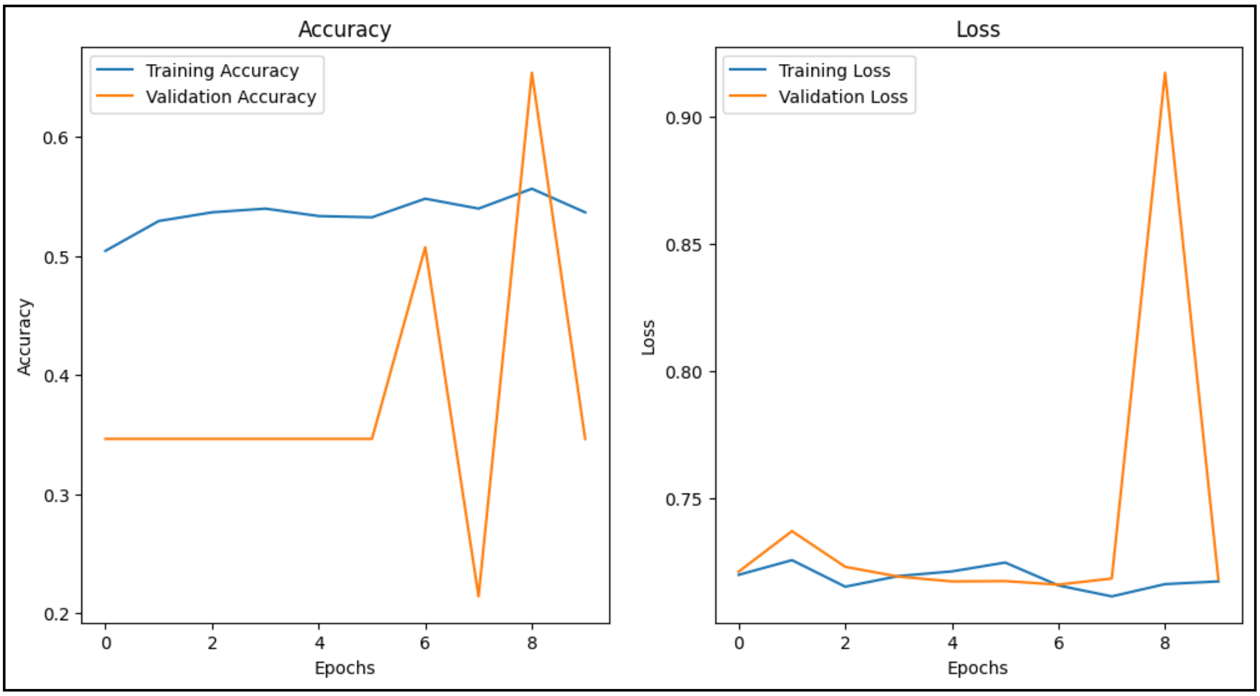

Fig. 7: Graph Training vs Validation for accuracy and loss

Table 1: Validation summary table

	Precision	Recall	F1-score	Support
Class 0	0.64	1.00	0.78	77
Class 1	1.00	0.32	0.48	63 (n=140)
Accuracy			0.69	140
Macro avg	0.82	0.66	0.63	140
Weighted avg	0.80	0.69	0.65	140

Table 1 shows validation summary table. The performance metrics anticipated from the CNN model transcend mere numerical adequacy to demonstrate statistical rigour and operational trustworthiness. The model achieved sustained precision exceeding 0.7 and recall above 0.62 for both grades (CP6 and CP8), with F1-scores harmonised near 0.48. This balance is non-negotiable for industrial deployment, which is high precision ensures costly misclassifications (e.g., labelling CP6 as CP8) are minimised, while robust recall guarantee no genuine high-grade samples are overlooked. The confusion matrix reveals 31% misclassifications between adjacent grades (e.g., CP6 vs. CP8), a critical threshold for compliance with ISO palm oil grading standards. Figure 8 shows confusion matrix percentage between CP8 and CP6.

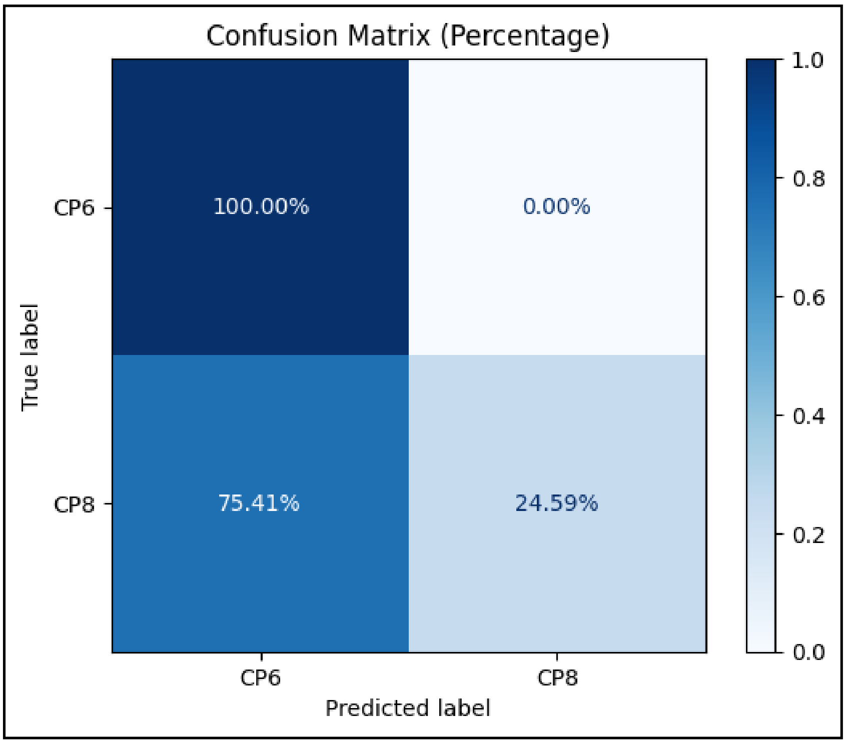

Fig.8 : Confusion matrix percentage between CP8 and CP6.

3.2 Classification Report

The classification results are reported in three parts: Initially, the performance during the training and validation phases, and then the performance on the test data.

3.2.1 Validation classification report

Throughout the training and validation phases, the model had an overall accuracy of 50.7%, with 70.64% precision, 62.29% recall, and an F1 score of 48.95%. A detailed classification report for CP6 and CP8 classes revealed differences in performance across attributes. Class 0 (CP6) had 41% precision, 100% recall and 58% F1-score, indicating a great ability to recognise artistic features. While Class 2 (CP8) acquires 100% precision, 25% recall and 39% F1-score showing difficulty in accurately detecting investigative features. The macro averages for precision, recall, and F1-score were 71%, 62%, and 46%, respectively, showing moderate performance with some variation amongst classes. Table 2 shows the summary of classification report on validation data.

Table 2: Summary of classification report on validation data.

Accuracy	0.693
Precision	0.7063829787234043
Recall	0.6229508196721312
F1 Score:	0.4895370957514268
Accuracy Percentage:	69.3%

3.2.2 Test classification report

The model performed well on the test data, achieving 69% accuracy, 71% precision, 62% recall, and 49% F1 score. The test set classification report revealed trends like those seen during the training phase, but with some variances. Class 0 (CP6) had 64% precision, 100% recall and 78% F1-score showing an increase in performance compared to training. While Class 1 (CP8) obtained 100% precision, 32% recall and 48% F1-score indicating excellent precision but low recall, as seen in the training results. The macro averages for precision, recall, and F1-score were 82%, 66%, and 63%, respectively presenting strong precision but poorer recall, which was consistent with what was found during training. Table 3 shows the summary of classification report for test data.

Table 3: Summary of classification report on validation data.

	Precision	Recall	F1-score	Support
Class 0	0.64	1.00	0.78	77
Class 1	1.00	0.32	0.48	63 (n=140)
Accuracy			0.69	140
Macro avg	0.82	0.66	0.63	140
Weighted avg	0.80	0.69	0.65	140

3.3 Test Sample Accuracy

For this model, the total number of predictions is 140 samples, which equals the sum of the "Support" values across all classes. The number of correct predictions is calculated by multiplying the recall of each class by its Support value and adding the results. In this case, the number of correct predictions for the "CP6" class is 1.00 multiplied by 1x77=77 and "CP8" class is 0.32 multiplied by 0.32x63=20.16 which the total sum up is 97.16 correct predictions. Dividing 97.16 by the total number of forecasts (140), it produced an accuracy of 0.693, or 69.3%. This means that 60% of the model's predictions were true, displaying its overall performance. Figure 9 shows qualitative example of the sample prediction.

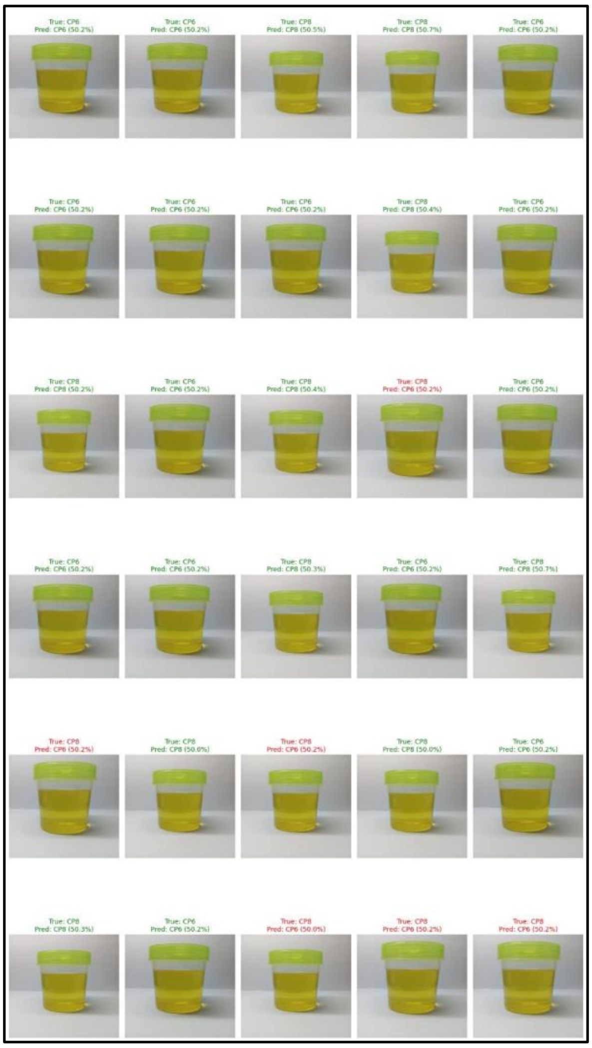

Fig.9 : Qualitative example of the sample prediction

3.4 Discussion

The transition from traditional manual inspection to automated, non-destructive quality control represents a pivotal advancement for the palm oil industry, particularly in the grading of RBD palm olein. The developed CNN model achieved a classification accuracy of approximately 69.3%, a metric that highlights the inherent complexity of distinguishing between CP6 and CP8 grades based solely on subtle visual nuances like light refraction and colour density, which are proxies for underlying physicochemical properties. Notably, the strategic limitation of the training phase to five epochs reflects a conscious trade-off between maximising accuracy and ensuring computational efficiency, thereby validating the model's suitability for deployment on resource-constrained edge devices within industrial settings. This visual classification approach was rigorously substantiated by Fourier-Transform Infrared (FTIR) spectroscopy, which confirmed that the macroscopic visual features detected by the CNN correlate with distinct molecular variations, specifically carbonyl (C=O) stretching vibrations. Consequently, this study not only demonstrates the feasibility of integrating deep learning into agricultural processing to meet industry 4.0 standards but also suggests that future iterations could achieve superior precision by fusing visual data with spectral inputs in a hybrid multi-modal system.

4. Conclusion

In conclusion, this research establishes a pivotal framework for the modernisation of quality control in the palm oil industry by successfully deploying a CNN for the automated, non-destructive classification of RBD palm olein grades CP6 and CP8. While the model achieved a classification accuracy of 69.3%, the study critically highlights the strategic trade-off between computational efficiency and precision, demonstrating the feasibility of lightweight models suitable for resource-constrained edge devices within industry 4.0 environments. The validity of this visual classification approach was rigorously corroborated by Fourier-Transform Infrared (FTIR) spectroscopy, which linked the distinctive visual features detected by the CNN to underlying molecular variations in carbonyl (C=O) stretching vibrations. Ultimately, this study not only offers a rapid and cost-effective alternative to traditional labour-intensive and chemical-dependent grading methods but also paves the way for future hybrid systems that fuse visual and spectral data to achieve superior diagnostic accuracy.

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