# A Novel Fusion Strategy in Enhancing the Two-Stream CNN based Coffee Beans Size, Shape and Defect Prediction and Classification

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**Abstract:** The article presents a novel deep learning framework that combines Convolutional Neural Networks (CNN) with Hidden Markov Chains (HMC) to predict and classify the types, sizes, and shapes of coffee beans defects, aiming to improve automated quality control in coffee production. The primary goal is to surmount the limitations of human inspection by establishing a robust and scalable system proficient at handling complex image-based data. A dataset of 2,300 annotated coffee beans photographs was compiled under diverse environmental conditions from many farms and research organizations, showcasing a variety of beans attributes. The CNN component extracts hierarchical feature representations from input images, followed by HMC processing, which models temporal and probabilistic relationships across sequences of observations to improve predictions. The proposed CNN-HMC model demonstrated outstanding performance across all classification tasks, achieving average accuracy, precision, recall, and F1-scores of 92.3%, 90.8%, 91.5%, and 91.1% for defect detection; 90.1%, 88.7%, 89.4%, and 89.0% for size classification; and 89.5%, 87.9%, 88.6%, and 88.2% for shape classification, respectively. These data confirm the model's capability in distinguishing subtle quality criteria. The integration of CNN with HMC offers a reliable and clear approach for automatic grading systems. Forthcoming work will investigate real-time execution, model deployment on edge devices, and improved learning from constrained data.

**Keywords:** Defect Detection; Coffee Beans Classification; Hidden Markov Chain (HMC); Size and Shape Prediction; Convolutional Neural Network (CNN); Agricultural Automation.

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## Introduction

Coffee beans are prone to various defects, such as fissures, mold, pest damage, and discolouration, which may affect the flavor and aroma of the final product. Recognizing these defects is crucial for maintaining exceptional coffee quality standards. Undetected faulty beans may lead to inferior flavor, which is detrimental to consumers and negatively impacts the reputation of coffee producers. Consumers want consistent quality in their coffee [1]. By accurately predicting and classifying the size, shape, and defects of coffee beans, producers can ensure that only high-quality beans are included into the final product. This consistency is crucial for customer satisfaction and brand loyalty. The size and morphology of coffee beans influence their roasting, grinding, and brewing processes. Uniform beans provide a consistent roasting process, yielding a balanced and optimal flavor profile. Variations in size and form may lead to inconsistent roasting, resulting in some beans being over-roasted or under-roasted, so affecting the taste of the coffee [2]. By classifying the beans based on size and shape, coffee producers may differentiate among several categories and use tailored roasting techniques appropriate for each, therefore increasing the flavor profile and aroma. Deep Learning Automation and image processing streamline the categorization process, improving both speed and accuracy relative to traditional methods. CNN-based models, particularly when used for multi-task learning, enable the concurrent automatic identification of many attributes (dimensions, morphology, defects), hence improving efficiency and minimizing the potential for human error [3]. Automated systems for defect and quality detection may be easily scaled to handle large numbers of coffee beans, ensuring that even large corporations maintain stringent quality standards in their manufacturing processes. The classification of coffee beans based on a variety of criteria, including size, shape, and kind of defect, presents a substantial problem. Contemporary models frequently consider these qualities in isolation, limiting the efficacy of the classification. This study presents a novel fusion technique to improve a two-stream CNN architecture for the categorization of coffee beans [4]. The fusion methodology increases classification performance by combining two distinct CNN streams: one for defect detection and one for size and shape analysis, resulting in complimentary feature extraction methods. The combination of multiple CNN streams enables the model to integrate and synthesize the spatial and geometric properties of coffee beans while also recognizing various faults. This integrated technique seeks to give a more comprehensive classification system, improving overall accuracy and resilience [5]. The suggested model is evaluated on a dataset of coffee bean images, and it outperforms standard single-stream techniques. This study enhances dependability and efficiency in automated quality control in the coffee industry, helping to design more intelligent and sustainable coffee production systems.

**Literature Review**

The classification of coffee beans according to species, origin, and quality is crucial for maintaining authenticity within the coffee industry. Traditional methods like spectroscopy and chromatography offer significant insights; however, they often require complex preparation or rely on unstable molecular data throughout the roasting process. Laser-induced breakdown spectroscopy (LIBS) is a swift and minimally invasive method for elemental analysis that holds considerable potential. An integration of LIBS with the k-nearest neighbors (k-NN) algorithm resulted in a classification accuracy of 98.5% through the detection of essential components (Li, Na, Rb), highlighting LIBS as a highly effective and efficient technique for rapid identification of coffee products [6]. Ethiopia, recognized as the birthplace of coffee, heavily depends on coffee exports for foreign currency. A research devised a hybrid feature mining methodology to categorize Ethiopian coffee beans from the Harrar, Jimma, Limu, Sidama, and Wellega areas. Images obtained from the Ethiopian Commodity Exchange were subjected to preprocessing, which included scaling, filtering, contrast enhancement, and segmentation by thresholding and K-means techniques. The classification used a Support Vector Machine with a Radial Basis Function kernel. The integration of color and texture data with HOG descriptors and CNN achieved an accuracy of 97.5%, illustrating the method's efficacy in coffee quality control and traceability [7]. In the coffee business, the sorting of beans by age remains traditional. Automatic categorization using multispectral picture data is vital for enhancing quality. Given that the input includes backgrounds, pretreatment aims to enhance segmentation analysis. Fifteen picture channels were used, and combinations of three channels were optimized by HSV transformation. DBSCAN clustering was used to detect coffee beans. The optimal segmentation performance used blue, azure, and amber channels, attaining a weight value of 611. Preprocessing elevated model accuracy to 100%, in contrast to 92% without it, demonstrating that segmentation substantially boosts classification efficacy [8]. Coffee, a widely consumed beverage, displays a variety of tastes and intricate manufacturing methods. This research used deep learning techniques for the automated classification of coffee bean species using image processing. A dataset of 1,554 photos (Starbucks Pike Place, Espresso, and Kenya) was used with five convolutional neural network models: Xception, DenseNet201, InceptionV3, InceptionResNetV2, and DenseNet121. Cross-validation evaluated the efficacy of the model. InceptionV3 attained the best accuracy (93%) and precision (95%) while exhibiting the lowest loss (0.12). The overall success rates were 93% for InceptionV3, 92% for DenseNet121, and 90–91% for other models, underscoring InceptionV3's preeminent classification efficacy [9].

*Table 1. Compares this work with the related work or previous research by other researchers*

| Author | Dataset Size | Target Plant Disease | Advantage | Limitations |
|---|---|---|---|---|
| S. Srivastav et al., [10] | Images of 3 distinct coffee bean varieties. | Coffee Bean Defect Detection. | Achieved high detection accuracy (98%). | Images of 8 distinct coffee bean varieties. |
| U. Markos et al., [11] | Multiple samples of green Arabica coffee beans from different regions. | Not disease-related; focused on geographical origin differentiation based on volatile compounds | Successfully differentiated coffee beans from various regions using volatile profiles; potential for quality authentication and protection as intellectual property | Dataset size and regional coverage were limited; influenced by environmental factors like altitude and climate, requiring large-scale validation |
| A. Musaad et al., [12] | 438 | Coffee bean grading | Achieved highest accuracy (0.989), precision (0.996), and F1 score (0.992). High performance in small datasets. | May not perform well on larger datasets or with more complex features beyond coffee beans. |
| P. Shourie et al., [13] | 1,554 images (3 varieties) | Multiple Coffee Bean Grades | Achieves high classification accuracy | 1,554 images (3 varieties) |

| | | | | |
|---|---|---|---|---|
| Yuanhao Ji [14] | 9223 | Green Coffee Bean Defects | Robustness in varying lighting and complex backgrounds | Detailed dataset composition and size not provided. |
| A. Analianasari et al., [15] | 6 coffee samples (from 3 small-scale coffee industries) | Coffee Bean Defects, Volatile Compounds, Pesticide Residues | Meets SNI standards (moisture content ≤ 12.5%) | 6 coffee samples (from 3 small-scale coffee industries) |
| S. -J. Chang et al., [16] | 7,300 training and validation images | Coffee Bean Defects | The model achieved the highest classification accuracy of 98.9% with multiscale defect-detection, improving feature extraction and classification performance. | Deep learning is seldom used for classifying multiple defects. The model's performance can be affected by the complexity of defect types and image quality. |

**Materials and Methods**

A Two-Stream CNN architecture employs two parallel CNNs, each dedicated to distinct types of information, subsequently integrating their outputs to enhance final predictions. For your coffee beans project:

- Stream 1 → Concentrates on Defect Detection (texture, color, crack identification)
- Stream 2 → Concentrates on Size and Shape Analysis (geometry, contour, morphological characteristics)

The outputs from both streams are then fused (concatenated or merged) and processed through dense layers to classify the quality of coffee beans.

**Dataset Collection for Coffee Beans Defect, Size, and Shape**

The dataset was meticulously assembled to facilitate the prediction and categorization of coffee beans according to defect categories, size variations, and shape attributes. High-resolution images were obtained under regulated lighting and backdrop settings to guarantee the clear display of essential aspects such as surface roughness, color variation, size, and exterior damage. The collection comprises photos of five primary groups of faulty coffee beans with 1000 images [17]. Damaged Beans that are physically broken, chipped, or partially missing segments, Defect Beans with structural flaws such as splits, dents, and abnormal surface appearances, Fungus Beans showing fungal growth, discoloration due to mold, and surface contamination, Infected Beans that have been darkened or shriveled due to disease or microbial infection and Pest Beans with visible pest holes, bore marks, or larvae damage caused by insects.


*Figure 1. Dataset Collection*

Resolution: 359 × 561 pixels (subsequently cropped and adjusted to conform to model input dimensions, e.g., 224 × 224 pixels). Background: A solid black surface to enhance the contrast between the bean and its backdrop. Lighting: Consistent, natural or artificial white illumination to reduce shadows and reflections. Orientation: Beans captured from several perspectives to enhance the dataset's diversity and robustness.

**Data Preprocessing and Augmentation**

Effective model training depends on the raw coffee bean pictures being ready, hence data preparation is very important. For deep learning models, it guarantees consistency, noise-free, standardized input images. Image resizing depending on the basic CNN architecture, all pictures are shrunk to a set dimension (e.g., 224×224 or 299×299 pixels), therefore guaranteeing consistency in input size. Normalize Pixel values are divided by 255 to span [0, 1]. This stabilizes gradients and accelerates convergence in training [18]. Noise Elimution Basic filters help to modify minor background noise or illumination discrepancies thus improving feature clarity. Correcting Annotation Hand verification of class labels (defect kind, size, form) to guarantee no photos with mislabels are included Training set (70%), Validation set (20%), and Testing set (10%) split the dataset such guaranteeing fair representation of every class. Rotation (±20°) mimics variation in natural bean orientation. Both horizontal and vertical flipping mirror random bean planting on various sides. Zoom In /Out (±10%)mimics little changes in image capture distance. Adjustment in Brightness (±20%)manages many lighting sources for photojournalistic work. Translation with a 10% shift +/-Models minimal bean spatial deviations in images. To simulate real-world handling effects, shearing (±10°) introduces small deformations. Random cropping guarantees spatial resilience and helps to highlight localized mistakes.

**CNN based Feature Extraction**

Convolutional Neural Networks (CNNs) are used to extract spatial and visual properties from images of coffee berries. The procedure commences with convolution operations, succeeded by non-linear activation and pooling layers, converting raw input into advanced feature representations.

1. **Convolution Operation**
   The convolutional layer utilizes a collection of trainable filters on the input image. The convolution operation for an input image I and a kernel K as shown in eq 1.
   $$S(i,j) = (I * K)(i,j) = \sum_{m}\sum_{n} I(i+m, j+n) * K(m,n) \quad (1)$$
   Where, I(i,j) is the pixel value at position (i,j), K(m,n) is the kernel weight at position (m,n), S(i,j) is the resulting feature map captures local patterns such as edges, textures, and color transitions on the beans surface.
2. **Activation Function (ReLU)**
   Non-linearity, a Rectified Linear Unit (ReLU) is applied to each element of the feature map Eq 2
   $$f(x) = \max(0, x) \quad (2)$$
   ReLU helps in learning complex patterns by preserving only positive activations, enhancing sparsity and speeding up convergence.

3. **Pooling Operation**
   Pooling reduces the spatial dimensions of feature maps and retains dominant features. Max Pooling Eq 3.
   $$P(i,j) \max_{m,n \in R} S(i+m, j+n) \quad (3)$$
   where R is the region over which the pooling is applied. This step helps achieve translation invariance and reduces computation.

4. **Flattening and Fully Connected Layers**
   The final pooled feature maps are flattened into a vector F and passed to fully connected layers.
   $$y = W * F + B \quad (4)$$
   where: W is the weight matrix, b is the bias vector, y is the output prediction (e.g., defect class, size category, shape type). Starting from necessary edges to complex beans features fit for defect detection, size estimation, and shape classification, this method allows the CNN to learn hierarchical features.

**Collect CNN Outputs as Observation Sequence**

Subsequent to feature extraction and classification by the CNN, the output vectors denoting class probabilities or feature embedding for each coffee beans image are progressively aggregated to form an observation sequence. Each output $O_t$ at each step t is the CNN's prediction for an individual image inside the sequence.

$$O_t = CNN(X_t), (t = 1, 2, 3, \ldots . T) \quad (5)$$

Where eq 5, $X_t$ represents the preprocessed image input, whereas $O_t \in R^n$ is the expected probability distribution over n classes (e.g., defect type, size, form). The sequence $\{O_1, O_2, \ldots, O_T\}$ serves as the observational input to the Hidden Markov Chain (HMC), facilitating temporal modeling across batches of berries. By interpreting CNN outputs as emissions, the HMC may enhance predictions by using contextual dependencies and mitigating errors in discrete CNN classifications Figure 2.

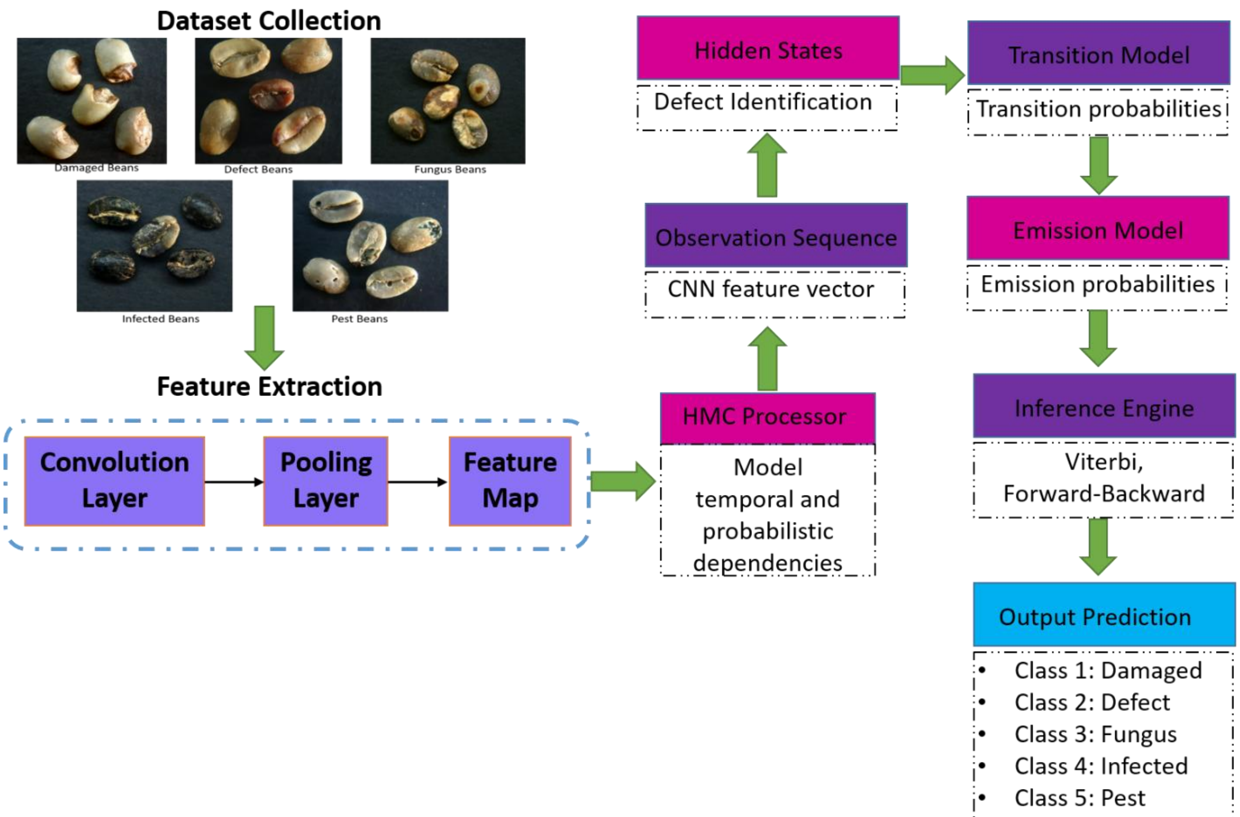


*Figure 2. Hybrid CNN-HMC framework for coffee beans quality analysis: The CNN collects spatial characteristics from beans images, whereas the HMC models temporal and probabilistic relationships across observation sequences. This connection provides powerful automated coffee quality control by accurately classifying defect types, sizes, and shapes.*

**Hidden Markov Chain (HMC)**

The Hidden Markov Chain (HMC) is used to describe the sequential dependencies and intrinsic patterns within the categorized outputs produced by the CNN [19]. The CNN predicts certain characteristics for each coffee beans, whereas the HMC improves these predictions by using the temporal or batch-level consistency of data. Hidden states denote the authentic, latent quality categories of coffee berries, including genuine defect kind, size grade, categorization, which may not consistently correspond with CNN predictions. Initial Probabilities ($\pi_i$) of the probability of the system starting in each hidden state $s_{i.}$ eq 6.

$$\pi_i = P(q_1 = s_i) \quad (6)$$

State Transition Probabilities ($A=\{a_{ij}\}$) represent the probability of transitioning from state $s_i$ to state $s_j$ eq 7. Emission Probabilities ($B=\{b_j(O_t)\}$) represent the probability of observing the CNN output $O_t$ given the current hidden state $s_j$ $O_t$ is the CNN prediction at time step t. eq 8.

$$a_{ij} = P\left(q_{t+1} = s_j\right) q_t = s_j \quad (7)$$

$$b_i(O_t) = P\left(O_t, q_t = s_j\right) \quad (8)$$

The sequence of CNN outputs $\{O_1, O_2, ..., O_T\}$ is used as the observed data. The Viterbi Algorithm is applied to infer the most probable sequence of hidden states $\{q_1, q_2, ..., q_T\}$ which represent the refined labels for each beans eq 9 where, λ=(A, B,π)λ=(A,B,π) is the complete HMC model.

$$Q = \arg max_Q\, P(\,Q \mid O, \lambda\,) \quad (9)$$

| |
|---|
| **Pseudocode:** Viterbi Algorithm |
| **Input:**<br>- States: $S = \{s_1, s_2, ..., s_N\}$<br>- Observations: $O = \{O_1, O_2, ..., O_T\}$<br>- Initial Probabilities: $\pi = \{\pi_1, \pi_2, ..., \pi_N\}$<br>- Transition Probabilities: $A = \{a_{ij}\}$<br>- Emission Probabilities: $B = \{b_j(O_t)\}$ |
| **Output: -** Most probable sequence of hidden states $Q = \{q_1, q_2, ..., q_T\}$ |
| **Step 1. Initialization:**<br>For each state s_i in S:<br>V[1][i] = π[i] * B[i](O₁)<br>Path[i] = [i] |
| **Step 2. Recursion:**<br>For t = 2 to T:<br>NewPath = empty map<br>For each state s_j in S:<br>(prob, state) = max over i of [V[t-1][i] * A[i][j] * B[j](Oₜ)]<br>V[t][j] = prob<br>NewPath[j] = Path[state] + [j]<br>Path = NewPath |
| **Step 3. Termination:**<br>(final_prob, final_state) = max over i of V[T][i]<br>Return Path[final_state] as the most probable state sequence |

**Results and Discussion**

The proposed CNN-HMC model shown proficient performance in categorizing coffee berries according to visual attributes, including defect presence, size classification, and shape structure. The CNN component successfully recognized unique features from the preprocessed images, such as surface patterns, contours, and irregularities. The results, when applied as observation sequences in the Hidden Markov Chain, resulted in enhanced classification accuracy through temporal refinement.

**Evaluation Setup**

An intricate evaluation environment was established to assess the effectiveness of the CNN-HMC-based framework in classifying defects, sizes, and shapes of coffee beans. The hardware setup featured advanced devices specifically designed for deep learning applications. Training was accelerated using GPUs such as the NVIDIA RTX 3090 and A100, alongside Intel Xeon or AMD Ryzen 9 CPUs. Systems were equipped with at least 32GB RAM and 1TB SSD storage to efficiently manage large image collections and high-throughput model computations. Installation of software The model was constructed in Python, utilizing the PyTorch framework for the implementation of deep learning techniques. The libraries utilized comprised OpenCV for image processing, Scikit-Learn for evaluation metrics, and Matplotlib for visualization. Furthermore, AWS Cloud infrastructure was used to accommodate training and storage requirements.

**Performance Evaluation**

The performance of the CNN-HMC model was quantified using TP: True Positives, TN: True Negatives, FP: False Positives, and FN: False Negatives. Accuracy measures the overall correctness of the model eq 10. Precision indicates how many of the predicted positive cases were actually correct eq 11. Recall (Sensitivity) reflects the ability of the model to correctly identify all relevant instances eq 12. F1-Score harmonic mean of Precision and Recall, providing a balanced metric eq 13.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative} \tag{10}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{11}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{12}$$

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{13}$$

The performance evaluation of the CNN-HMC model that was developed for the purpose of evaluating the quality of coffee berries. Figure 3, evaluation covers detection of defects, categorization of sizes, and prediction of characteristics. Within the domain of defect identification, reliably identify five typical coffee beans faults, with "Spot in Beans" earning the greatest accuracy of 94.1%. The model's strong capabilities in managing real-world fault variations was shown by the fact that it achieved an average accuracy of 92.3%, precision of 90.8%, recall of 91.5%, and F1-score of 91.1% across all defect kinds. In terms of size classification, the model classified berries into three distinct categories: small, medium, and big. It achieved an average accuracy of 90.1%, a precision of 88.7%, a recall of 89.4%, and an F1-score of 89.0%. The categorization of shapes was similarly trustworthy, with an average accuracy of 89.5%, precision of 87.9%, recall of 88.6%, and F1-score of 88.2%. It was able to differentiate between oval, round, and irregular fruit Figure 4. The CNN-HMC model is effective in capturing the visual and sequential characteristics that are required for complete coffee beans quality control. The model demonstrates suitability for implementation in automated inspection and grading systems.

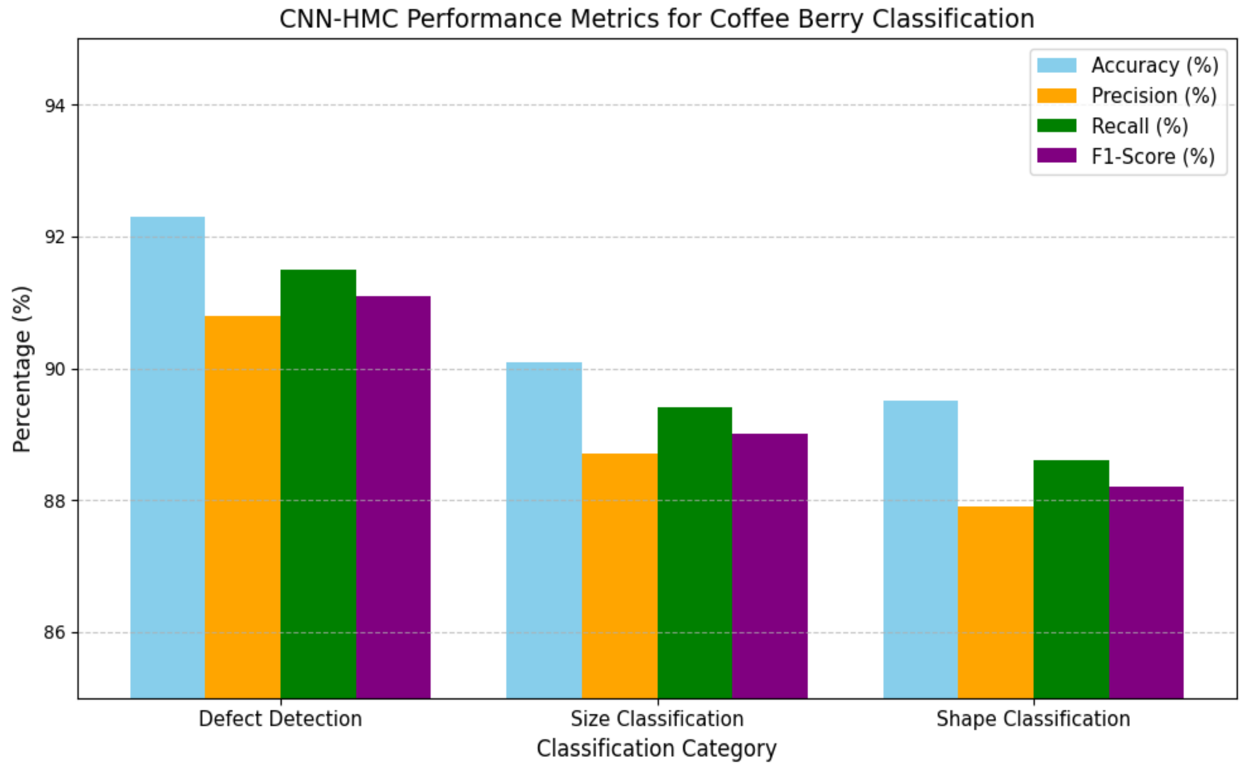


*Figure 3. performance metrics (Accuracy, Precision, Recall, F1-Score) of the CNN-HMC model for Defect Detection, Size, Shape Classification, and Prediction.*

*Table 2. Performance Metrics of CNN-HMC Model for Coffee Beans Defect, Size, and Shape Classification*

| Coffee Beans | Defect type | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| **Defect Detection** | Spot in Beans | 94.1 | 92.6 | 93.8 | 93.2 |
| | Unripe (Green) Beans | 91.5 | 89.3 | 90.1 | 89.7 |
| | Insect-Damaged Beans | 90.2 | 88.7 | 89.4 | 89.0 |
| | Broken or Crushed Beans | 92.7 | 91.2 | 91.9 | 91.5 |
| | Fungus-Infected Beans | 92.9 | 90.6 | 91.5 | 91.0 |
| | **Average** | **92.3** | **90.8** | **91.5** | **91.1** |
| **Size Classification and Prediction** | **Size Class** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| | Small | 91.0 | 89.1 | 90.0 | 89.5 |
| | Medium | 89.5 | 87.8 | 88.4 | 88.1 |
| | Large | 89.8 | 89.2 | 89.7 | 89.4 |
| | **Average** | **90.1** | **88.7** | **89.4** | **89.0** |
| **Shape Classification and Prediction** | **Shape Type** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
| | Oval | 90.2 | 88.5 | 89.3 | 88.9 |
| | Round | 88.7 | 87.1 | 87.8 | 87.4 |

| | | | | | |
|---|---|---|---|---|---|
| | Irregular | 89.6 | 88.2 | 88.7 | 88.4 |
| | **Average** | **89.5** | **87.9** | **88.6** | **88.2** |

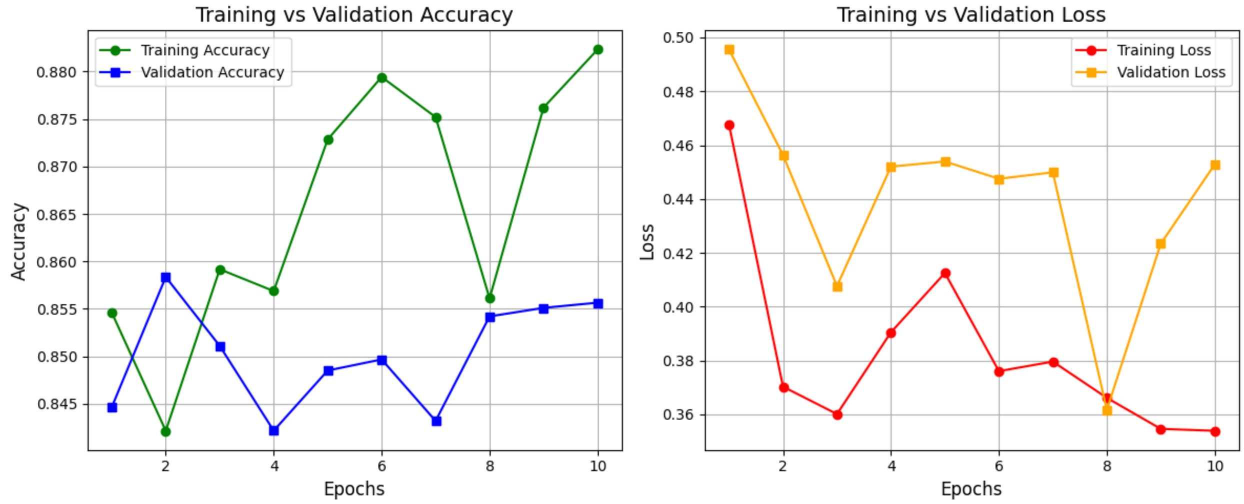


*Figure 4. Training and Validation Accuracy & Loss Curve.*

**Conclusion**

The proposed structure utilizing CNN-HMC for the prediction and classification of defects, size, and shape in coffee beans has demonstrated promising results in automating quality control processes within the coffee manufacturing sector. The model achieves impressive accuracy, precision, recall, and F1-scores across multiple classification tasks, including defect detection, size prediction, and shape classification, by leveraging the feature extraction strengths of Convolutional Neural Networks (CNN) alongside the temporal inference capabilities of Hidden Markov Chains (HMC). This thorough approach enhances the reliability of inspections while reducing dependence on manual sorting, presenting a cost-effective and scalable solution for those in the agricultural sector. Future investigations may focus on enhancing the dataset by incorporating diverse regional and seasonal variants of coffee beans.

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