STATISTICS, OPTIMIZATION AND INFORMATION COMPUTING
Stat., Optim. Inf. Comput., Vol. **12**, July 2024, pp 1004–1018.
Published online in International Academic Press (www.IAPress.org)

Categorization of Dehydrated Food through Hybrid Deep Transfer Learning Techniques

Sm Nuruzzaman Nobel [1], Md. Anwar Hussen Wadud [1], Anichur Rahman [2,*], Dipanjali Kundu [2], Airin Afroj Aishi [3], Sadia Sazzad[2], Muaz Rahman[2], Md Asif Imran[1], Omar Faruque Sifat[1], Mohammad Sayduzzaman[2], T M Amir Ul Haque Bhuiyan[1]

[1]*Department of CSE, Bangladesh University of Business and Technology, Dhaka, Bangladesh*
[2]*Department of CSE, National Institute of Textile Engineering and Research (NITER), Constituent Institute of the University of Dhaka, Savar, Dhaka-1350, Bangladesh*
[3]*Department of CIS, Daffodil International University, Dhaka, Bangladesh*
[4]*Department of EEE, National Institute of Textile Engineering and Research (NITER), Constituent Institute of the University of Dhaka, Savar, Dhaka-1350, Bangladesh*

Abstract The essentiality of categorizing dry foods plays a crucial role in maintaining quality control and ensuring food safety for human consumption. The effectiveness and precision of classification methods are vital for enhanced evaluation of food quality and streamlined logistics. To achieve this, we gathered a dataset of 11,500 samples from Mendeley and proceeded to employ various transfer learning models, including VGG16 and ResNet50. Additionally, we introduce a novel hybrid model, VGG16-ResNet, which combines the strengths of both architectures. Transfer learning involves utilizing knowledge acquired from one task or domain to enhance learning and performance in another. By fusing multiple Deep Learning techniques and transfer learning strategies, such as VGG16-ResNet50, we developed a robust model capable of accurately classifying a wide array of dry foods. The integration of Deep Learning (DL) and transfer learning techniques in the context of dry food classification signifies a drive towards automation and increased efficiency within the food industry. Notably, our approach achieved remarkable results, achieving a classification accuracy of 99.78% for various dry food images, even when dealing with limited training data for VGG16-ResNet50.

Keywords Dry Food, VGG16, ResNet50, Classification, Datasets, Hybrid, Deep Learning, Transfer Learning

AMS 2010 subject classifications 97P50, 97R40

DOI: 10.19139/soic-2310-5070-1896

1. Introduction

The categorization of dry fruit images has become a fundamental problem in the domain of computer vision, given their widespread consumption, nutritional values, and commercial significance. Accurate and efficient identification of dry fruits can streamline quality control processes, enhance food authentication, and optimize supply chain management, ultimately benefiting both producers and consumers. Therefore, the accurate and efficient classification of dry fruits is of great interest to researchers and industries involved in the food processing and packaging sectors. Conventional approaches to dry fruit classification have predominantly depended on human inspection, expert knowledge, and elementary image processing. Nonetheless, these techniques are subjective, lack scalability, and demand substantial labour, rendering them less appropriate for contemporary requirements.

*Correspondence to: Anichur Rahman (Email: anis_cse@niter.edu.bd). Department of CSE, National Institute of Textile Engineering and Research (NITER), Constituent Institute of the University of Dhaka, Savar, Dhaka-1350, Bangladesh.

ISSN 2310-5070 (online) ISSN 2311-004X (print)

In recent times, notable progress in deep learning and Convolutional Neural Networks (CNNs) has revolutionized the realm of image categorization, outperforming conventional methods and attaining exceptional precision and efficiency [1].

In light of these obstacles, advanced machine learning approaches which can be weighted and non-weighted. In study [2] authors developed a weighted version of the Bayesian predictor and examined the updated result corresponding to different scenarios. Nowadays notably CNNs, have surfaced as formidable instruments for image classification endeavours. CNN has exhibited its proficiency in grasping hierarchical attributes from extensive datasets, empowering them to autonomously discern distinctive patterns and representations in images. The research paper "Dry Fruit Image Classification" underscores the critical importance of image analysis and artificial intelligence techniques in automating and improving the accuracy of dry fruit identification. Image processing enables the extraction of essential visual features, such as shape, color, and texture, facilitating efficient categorization. Machine learning algorithms, particularly CNNs, effectively handle the inherent variability in dry fruit images, making them invaluable tools for scalable and reliable classification tasks. In this paper [3, 4], the result shows that the developed image processing technique and assortment segment can be used to categorize fruits based on their dimension and complexion features with success rates ranging from 82 percent to 100 percent. The document [5] explores various digital imaging methods such as compilation of images, preprocessing, breakdown, and attribute extraction and proves that computer vision systems have the capacity to be employed for external quality assessment of food and agricultural commodities by examining the visual attributes of the items. In [6], authors show that machine learning (ML) algorithm is capable of greatly improving the precision and efficacy of fruit categorization or grading systems by leveraging their ability to analyze large amounts of data and extract meaningful patterns and relationships.

This research study, “Dry Fruit Image Classification” presents a customized model that combines two cutting-edge DL models, VGG16 and ResNet50, for the task of categorizing dry fruit images. The dataset used for training and evaluation is named “Dry Fruit Image Dataset” and consists of 11,500 images, which are classified into 12 classes representing different types of dry fruits [7]. In order to ensure a fair assessment of its performance, the model adheres to a conventional procedure that divides the dataset primarily (80 percent) for the purpose of training and the remaining for testing purposes. This division enables the model to gain knowledge from the majority of the data while evaluating its capacity to extrapolate samples that have not yet been observed. Prior to feeding the images into the model, image pre-processing steps are taken. Among these steps, the resizing function is used to standardize the dimensions of all images. This ensures that the input images have a consistent size, which is vital for the DL model's architecture to process the data effectively. In classification tasks, this step is crucial because it enables the model to comprehend the categorical labels and produce precise predictions during training and testing. The model's training process is further optimized using the popular Adam optimizer, known for its adaptive learning rate and efficient weight updates based on the gradient's first and second moments. Combining VGG16 and ResNet50 results in the customized model. Well-known DL architectures VGG16 and ResNet50 each have distinctive qualities that can work well together in the categorization of dry fruits challenge. In order to make use of each architecture's advantages and achieve greater overall performance than utilizing either model alone, the researchers combined these models [8].

In the other studies for “dry fruit image classification”, a wide range of ML techniques and models can be employed to achieve accurate and effective classification. In this study [9], the CNN algorithm is utilized to identify the appearances of fruit and contribute an effective system for segmenting. The suggested model combines max pooling and average pooling methods to improve generalization in the CNN, resulting in enhanced accuracy. The paper [10] suggests a system for classifying fruit images using DL models such as CNN, Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM). A dataset of fruit photos was used to test the suggested system, and the findings revealed that it was capable of producing accurate quantitative analysis. In another similar research [11], the author leveraged the RNN, and LSTM for predicting the rotation of crops. This study [12] shows that fruit image classification is based on a lightweight neural network MobileNetV2 with a transfer learning technique, which allows the researchers to achieve a high classification accuracy. The authors in [13] investigated and contrasted various approaches to the issue of DL-based picture categorization with data augmentation. The purpose of data augmentation is to increase the diversity and size of training data, which helps to generalize the model and reduce overfitting. A widely recognized supervised learning method for image categorization is the Support Vector Machine (SVM), which has been used in these papers [14, 15, 16, 17]. SVM is utilized to classify fruit images based on the features extracted from the color and texture of the images, achieving a classification accuracy of 95.3%. The use of SVM in this paper demonstrates its effectiveness in fruit classification and its potential application in the fruit industry and supermarket settings. When compared to an artificial neural network (ANN)–based system, the suggested SVM-based fruit categorization system is found to have higher accuracy. The Random Forests (RF) algorithm has been demonstrated in this paper [18] to outperform other methods, such as ANN and SVM, when it comes to classifying fruits. The RF algorithm offers superior accuracy than various other strategies, according to tests done on 178 fruit images. From the above discussion, this paper's contributions are as follows—

- To present reinforces that leveraging a combination of VGG16 and ResNet50 can be a promising approach to achieve superior performance in dry fruit image classification, fostering advancements in computer vision applications and food industry automation.
- Signify the ability of this custom model to considerably enhance the efficiency and precision of dry fruit image categorization, offering practical implications for food processing, quality control, and consumer satisfaction in the food industry.
- The incorporation of cutting-edge DL architectures and methodologies demonstrates the research paper's valuable contribution to the progress of image classification techniques, particularly concerning the domain of dry fruit categorization.
- Additionally, this research underscores the importance of adopting customized models that suit the specific requirements of the problem domain, offering insights into the design and development of effective machine-learning solutions.

The remainder of this paper is presented as detailed: Section 2 details a study of the pertinent literature in the field of food image classification and highlights the current state-of-the-art techniques. In Section 3, we outline the methodology adopted in this study, including dataset preparation, model architecture selection, and performance metrics. Section 4 illustrates the experimental findings, which are further presented in detail. Lastly, Section 5 concludes the paper, summarizing our contributions and outlining potential avenues for future research.

2. Background Study and Related Works

2.1. Background

Dry fruit image classification has become a vital pursuit in computer vision due to its practical implications for quality control, food authentication, and supply chain management. Traditional methods relying on human inspection and basic image processing lack scalability and accuracy. Recent advancements in DL, particularly convolutional neural networks, offer a promising alternative. CNNs excel in extracting intricate patterns from extensive datasets, enhancing classification precision. This study introduces a tailored model merging VGG16 and ResNet50 architectures for efficient dry fruit image classification, aiming to revolutionize food industry processes [19].

2.2. Literature Reviews

This literature review summarizes various studies on using advanced techniques to improve food classification, quality assessment, and nutrition. The researchers explored machine learning [20], hyperspectral imaging, and X-ray methods for tasks like bean and fruit classification, foreign object detection, and origin identification of foods. These studies contribute to enhancing food technology and safety through innovative approaches. As the dataset sometimes contained uneven and imbalanced samples, study [8] explains a method called SGBBA, which can handle highly inconsistent datasets with outstanding accuracy. Khan et al. [21] meticulously examine dry bean classification using machine learning techniques, showcasing XGBoost's (XGB) superiority, with ACC values of 95.40% when combined with ADASYN and 93.00% without ADASYN. Their work underscores the significance of ShapeFactor2 and Minor Axis Length as pivotal features for accurate classification. This study not only advances agricultural technology but also paves the way for future research in crop classification. In another study, Nirere et al. [22] conducted an in-depth study utilizing hyperspectral imaging for dried wolfberry fruit classification, employing varied preprocessing methods and classification algorithms. Significant classification accuracy enhancements (up to 6.7%) were observed through SG and SNV preprocessing. Notably, the hybrid GWO-LS-SVM model demonstrated exceptional performance with 97.67% calibration and 96.66% prediction accuracy, highlighting hyperspectral imaging's potential for advanced food quality assessment. Nonetheless, PCA's limitations in delineating class boundaries were acknowledged. The study underscores preprocessing and optimization's pivotal role in prediction accuracy, offering insights for practical food safety applications. Future directions may encompass broader sample inclusion and model versatility testing. Again, Kipli et al. [23] analyzed the effects of CNN in counting palm oil trees with the limitations and possibilities of CNN in this field. According to the analysis, the best accuracy was achieved by implementing LeNet-based CNN for well-organized palm trees with a 99.0% accuracy score. Further, Shah et al. [24] proposed a deep-learning model for the classification of barley from color images with an accuracy of 94%.

In the study by Monteiro et al. [25], a novel food classification system was applied to analyze dietary patterns in Brazil. Ultra-processed foods (group 3), known for their high energy density and low nutrient quality, constituted a notable portion of caloric intake, particularly in higher-income households. These foods were linked to unhealthy consumption behaviours, such as snacking and excessive liquid calorie intake. The study advocates for public health interventions, including regulations, to counteract the rise of ultra-processed products and preserve nominally processed foods (group 1) and pre-prepared ingredients (group 2). Prabowo et al. [26] introduce the Colorimeter CK20.1 prototype, utilizing the TCS3200 colour sensor and Arduino Mega-2560, showing promise for commercial potential. While colour visualization similarities exist, significant differences ($p < 0.01$) and low R2 values in CK20.1's correlation with ColorFlex EZ raise accuracy concerns. Further refinement is essential for precise colour measurement despite initial strides in methodology and validation with ColorFlex EZ. This study underscores the need for coding enhancements and validation against established colourimeters in the pursuit of reliable colour measurements for dry foods. In their recent work, Liu et al. [27] introduced a deep learning model YOLO designed to recognize objects in flow meter readings. This approach was implemented on an IoT node, enabling efficient flow meter monitoring while minimizing data storage requirements. The novel algorithm demonstrated an impressive accuracy rate of 95.35% when tested with a real-time flow meter image dataset consisting of 1248 images. In another similar work, Degu et al. [28] combined YOLO-V3 and ResNet50 to classify images. They utilized the YOLO-V3 algorithm to segment regions of interest and employed ResNet50 for categorizing images with an impressive 98.7% accuracy. This achievement has potential applications in farm settings, particularly in the detection of cattle diseases. Similarly, Kwon et al. [29] introduced a method for the simultaneous identification of external objects in packaged foods using X-ray image analysis, focusing on irregular texture patterns. Their approach involved one-class classification and enhancing contrast through positive responses of zero mean images. The methodology demonstrated high detection rates for materials like glass, ceramic, and metal (98%) with minimal false positives. However, performance varied with object density and size, showing limitations for smaller and lower-density objects (e.g., Teflon, Rubber).

In another significant work, Steinkraus et al. [30] highlight the nutritional benefits of fermented foods, focusing on strategies to enhance protein and vitamin content. They emphasize the transformative effect of fermentation on substrates like rice, as seen in Indonesian tape ketan, which not only doubles the protein content but also selectively enriches essential amino acids. The authors underline the significance of fermented beverages like Mexican pulque and kaffir beer, which exhibit substantial increases in vitamins during fermentation. Additionally, the study underscores the fuel-saving aspect of fermented foods, reducing cooking times and thereby addressing a crucial concern, especially in resource-limited settings. Imran et al. advocate for further investigations to fully comprehend the potential of these approaches in improving global nutrition. There are environmental effects also which could be brought a bad result if the image processing techniques face difficulties in predicting the proper result. Air and temperature can distort the result. In the paper [31] authors proposed a unique model for improving the visual quality of the images where the sequences of images are affected by atmospheric turbulence.

In similar research, Pan Gao et al. [32] effectively employ near-infrared hyperspectral imaging and advanced machine learning techniques to classify narrow-leaved oleaster fruits by geographical origin. Using PCA and discriminant models, the study achieves high classification accuracies exceeding 90%, with promising results from deep CNN models comparable to PLS-DA and SVM models. Effective wavelength selection enhances model performance, showcasing the potential of hyperspectral imaging and machine learning for accurate origin detection and food quality control. However, different researchers use numerous methods to analyze data channels. Using PCA and discriminant models, the study achieves high classification accuracies exceeding 90%, with promising results from deep CNN models comparable to PLS-DA and SVM models. Effective wavelength selection enhances model performance, showcasing the ability of hyperspectral imaging and ML techniques for accurate origin detection and food quality control. However, different researchers use numerous methods to analyze data channels. When data is imposed in those models, channels face DDoS attacks, which must be considered as an issue of data processing. The paper, [33], handled those situations with the help of SDN over the IoT networks. Authors from paper [34] introduced two new methods named NAC and NAP to work with this situation. When data is computed in a cloud-based manner, security becomes an issue where blockchain implementation is a solution. The study [35] explains cloud-based data security in a decentralized manner. In study [36], Federated Learning is introduced with AI and XAI technology, which cannot transfer the raw data to the system, thus ensuring data transfer and processing accuracy. As this is maintained in a communicative scenario, it can minimize several limitations. When the data is decentralized, the criticality becomes so strong, that it can be removed by ICN-IoT [37] merging with FL to ensure more security and privacy. Researchers in [38] proposed a model called "ConvNet" that can detect several faces with different emotions collaborating with CNN; this model succeeds in achieving an accuracy of 98.13%. Exploring recent advancements in date fruit classification [39], emphasizing a novel dataset collected from primary environments. With 27 classes and 3228 images, the study employs a five-stage experimental approach, incorporating traditional machine learning, deep transfer learning, fine-tuning, and regularization. The methodology yields impressive results, achieving a validation accuracy of 97.21%. The dataset's uniqueness lies in its multiplicity of items, sourced from farms and shops. The study contributes valuable insights into date fruit classification, with implications for agriculture, commerce, and health sectors. The accuracy of 98.67% using Softmax classifier accumulated with CNN is obtained in paper [40] where CNN brings a tremendous result when it merges with the feature extraction algorithm.

In summary, according to different knowledge-based techniques and models, the mentioned studies bring numerous informative and potentially useful assessment that incorporates all of the technologies under consideration. A number of technical challenges are being faced by the researchers who are working with Machine Learning, DL, and Federated Learning. Among those, our approach, called Hybrid DTL, can be considered a modern concept that can efficiently classify dry food, which remains a challenging study in modern research.

3. Materials and Methodology

This paper presents the development process of our proposed model, detailing its methodology design. The focus is on categorizing the preprocessing of dried fruits, introducing the suggested model, and classifying different types of dried foods. The paper concludes by illustrating and elucidating the functioning of the suggested model and approach in Fig. 1.

3.1. Datasets

A dataset is a compilation of information used in this study. Various methods were employed to extract important details from different papers to enhance the quality of this research. The dataset consists of 11,500 image records,

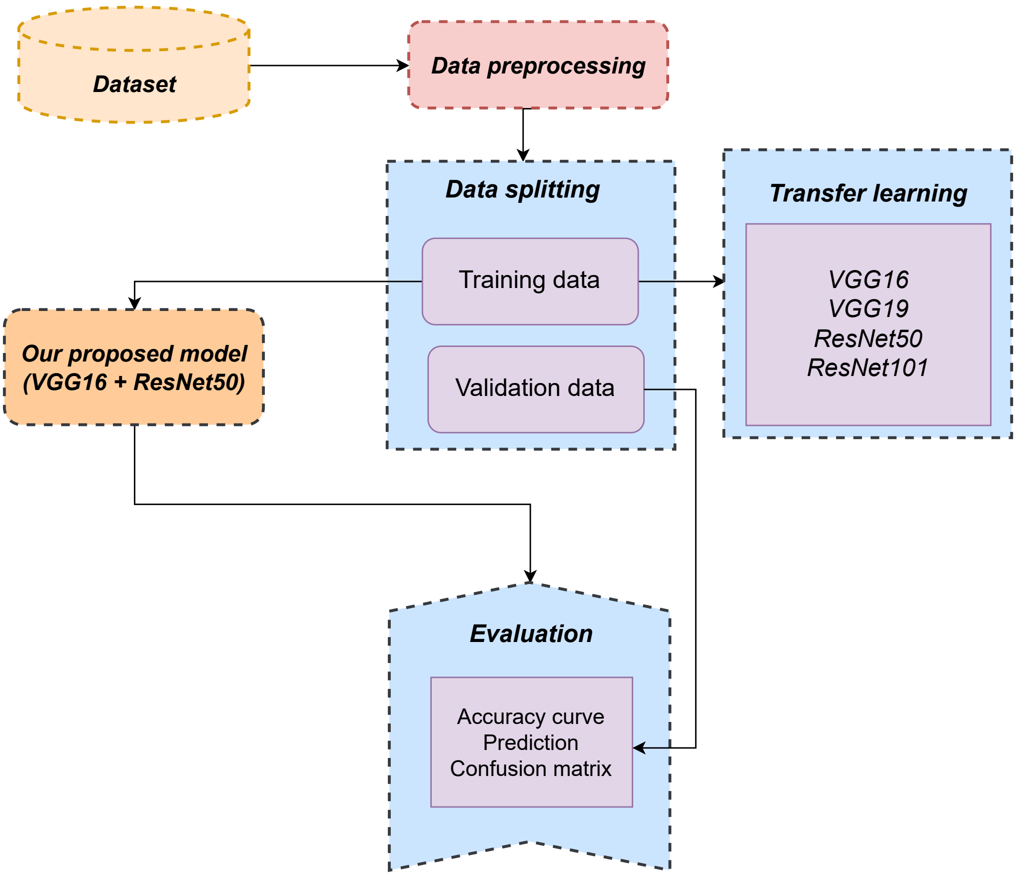

Figure 1. Workflow of the Proposed Methodology for Dry Food Classification

organized into twelve distinct categories. We offer detailed explanations for each of these categories, outlining the process step by step.

3.2. Data Pre-processing

The first step in the processing of the dried fruit image in this section is to preprocess the original buildup image. The initial image size can vary significantly, and the effectiveness of the processing is higher for images that are clear and well-defined. Since the image is collected from different sources, its size and shape can differ. To address this, the image is initially resized to dimensions of 224 by 224 pixels with three color channels. The shape of the image is adjusted as well. Each image is categorized, and the array is modified accordingly. In our projects, we utilize a grayscale model to convert color images. Ultimately, the project's output image size remains at 224 by 224 pixels with three color channels.

3.3. Model Development

In our study, we utilize various transfer learning and hybrid models to classify dry food items following thorough data preprocessing. The process of training a model involves several techniques and here we will concentrate on the application of pre-existing models to new tasks. Typically, extensive datasets like ImageNet are employed to initially train transfer learning models. Hybrid transfer learning involves the simultaneous use of two models. Specifically, we make use of established transfer learning models like VGG16, VGG19, ResNet50, and EfficientNetV2. Additionally, we work with a pre-trained hybrid model named VGG16-ResNet50 in Fig. 2.

3.3.1. Proposed Hybrid Model: The VGG16 convolutional neural network architecture is characterized by its deep structure consisting of 16 layers. It comprises 3x3 convolutional layers, max-pooling layers, and other types of layers.

VGG16 is popular for its simplicity and efficiency in image recognition tasks. Another CNN architecture known as ResNet50 is part of the ResNet family, which introduced the concept of skip connections or residuals to address the vanishing gradient problem in very deep networks. This allows ResNet50 to handle deeper structures effectively by enabling the learning of residual mappings. To create a hybrid model combining the strengths of VGG16 and ResNet50, one approach is to utilize the initial layers of VGG16 for extracting features from the input data. Then, the remaining blocks from ResNet50 can be added to the model for further processing. This hybrid model aims to benefit from ResNet50's ability to handle deep networks and mitigate gradient issues, while also leveraging VGG16's straightforward feature extraction capabilities. The hybrid model's classifier consists of a flat layer and a dense layer with 12 neurons. Since the task involves multi-label classification with a single output neuron, the classifier employs the softmax activation function to produce the desired predictions.

3.3.2. Transfer Learning Model: The article explores the application of transfer learning models in the context of DL and computer vision, specifically focusing on a binary classification problem related to detecting fire. The central approach involves utilizing pre-trained models that have been adapted to the specific task at hand distinguishing between instances of fire and non-fire. This approach leverages the knowledge these models have gained from a different but related domain, saving considerable time and effort compared to building models from scratch. The study employs five established deep CNN models – ResNet50, DenseNet201, MobileNetV2, InceptionV3, and Inception-ResNetV2 all of which have undergone prior training. The pre-trained models are fine-tuned using data related to fire detection. These models have already been trained on extensive datasets for various tasks, enabling them to apply their acquired expertise to address new and specific problems. In the experiment, the pre-trained models are imported and enhanced with a fully connected output layer (classifier). This newly added classifier consists of a flat layer and a dense layer comprising 12 neurons. The classifier employs the softmax activation, given that there is only one output neuron, aligning with the multi-label classification nature of the problem. To facilitate model training and evaluation, the overall data is split into two subsets: 80% training and the remaining 20% as validation set. This division enables effective learning and execution-ability of the model's performance. Authors from study [41] designed a "MultiNet" infrastructure relying on a transfer learning model that can consider different breast cancer images and classify the category of devices accurately.

3.4. Classification Process

The study proposes a novel approach to improve classification performance using features obtained from the VGG16-ResNet50 model. Instead of directly predicting class labels, the retrieved features are enhanced through a range of fully connected operations. These operations consider various combinations of features from VGG16-ResNet50. To further boost classification performance, batch normalization, and dropout layers are strategically placed among the fully connected operations. The inclusion of batch normalization stabilizes the learning process, reducing the need for extensive training epochs. The dropout layer regulates learning, mitigating overfitting issues and ultimately enhancing the model's generalization capability.

4. Result Analysis AND Discussion

4.1. Result Analysis

4.1.1. Evaluation Metrics: The ability of the proposed model on the validation set is depicted in the confusion matrix. This matrix is structured such that the predicted class is depicted in columns, whereas the actual class is illustrated in rows. The matrix values reflect the count of samples that were accurately or inaccurately classified. The results reveal that the proposed model gained an impressive precision of 99.78%, accurately classifying nearly all samples in the validation set. The model's error rate was found to be remarkably low, merely 0.22%. Notably,

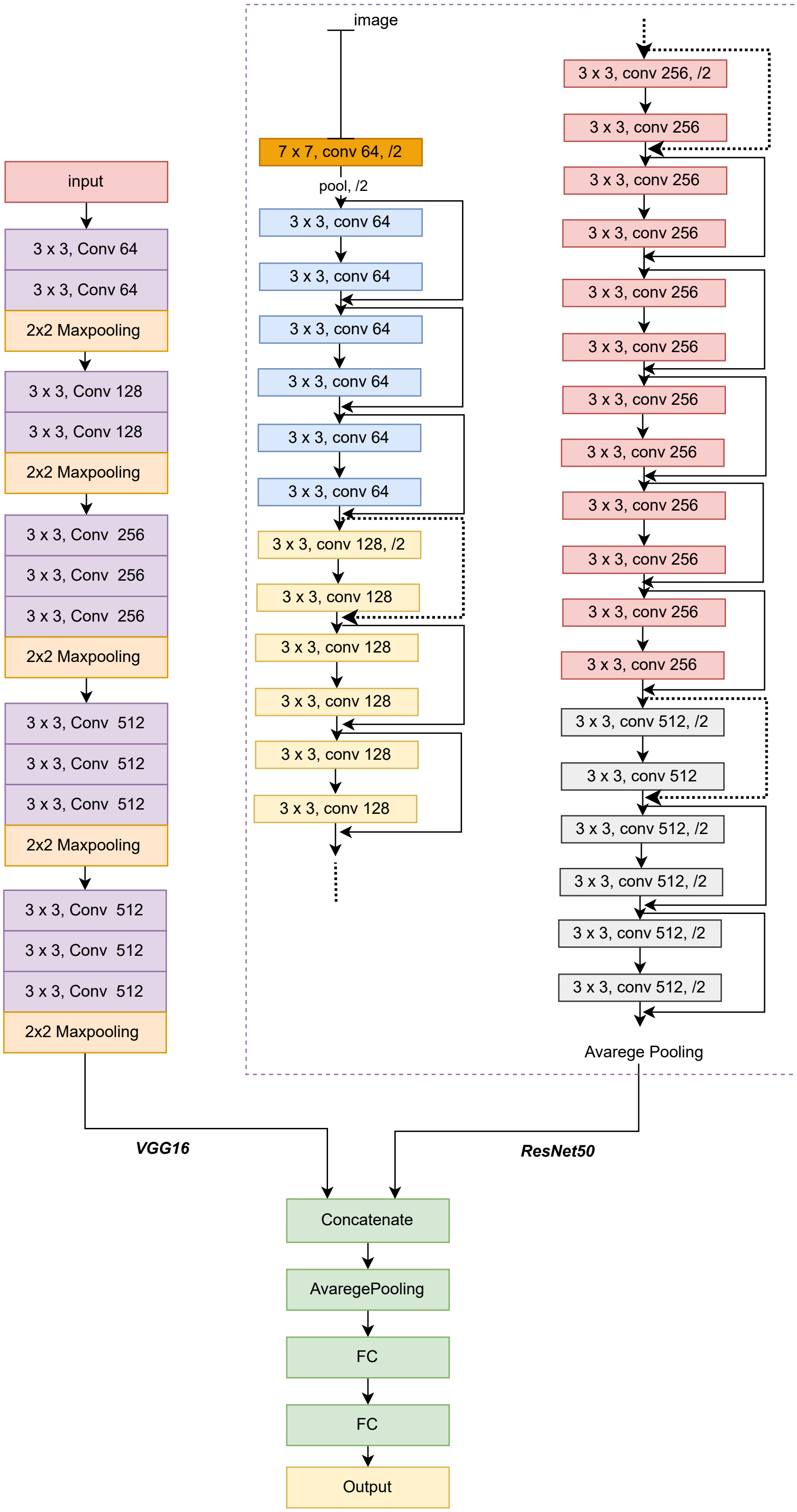

Figure 2. Proposed Hybrid Architecture for Image Classification Task

the most common miscategorization occurred between Almond Mamha and Almond Regular, as well as between Raisin Black and Raisin Premium. This suggests that the model might encounter challenges distinguishing between these specific types of nuts and raisins. Overall, the confusion matrix demonstrates that the suggested model serves as a highly accurate classifier for dry food items. With an accuracy rate of 99.78% and minimal errors, it exhibits remarkable performance. Further observations from the confusion matrix include the following:

- The proposed model achieved perfect classification for the classes Almond Mamha, Cashew Jumbo, Fig Jumbo and Raisin Black.
- There were a few misclassifications between the classes Almond Regular, Almond Sandra, Cashew Regular and Raisin Premium.
- The model's overall accuracy was exceptionally high, indicating its suitability for dry food item classification. The insights gained from the confusion matrix are valuable for enhancing the proposed model's performance. By identifying areas prone to errors, these observations can aid in refining the model and optimizing its accuracy.

4.1.2. Performance analysis: To present a comprehensive investigation into the Dry Food Dataset, utilizing various DL models such as VGG19, VGG16, ResNet50, and ResNet101 and a novel proposed model that combines VGG16 and ResNet50. The main goal is to achieve accurate classification performance of different dry food categories as shown in Fig. 3. The models are evaluated based on their training and validation accuracies to gauge their performance in Table 1.

Table 1. This table offers a thorough test in the form of a well-designed test as part of our never-ending quest for scientific excellence. a list of comparisons:

Model	Train Accuracy	Valid Accuracy
VGG19	88.72%	68.72%
VGG16	95.65%	92.88%
Resnet50	99.45%	96.72%
Resnet101	98.12%	93.12%
Our proposed Model	99.99%	99.78%

- **VGG19**: VGG19 demonstrates a relatively high training accuracy of 88.72%, indicating it effectively fits the training data. However, the validation accuracy of 68.72% suggests that the model suffers from overfitting, performing poorly on unseen data.
- **VGG16**: VGG16 achieves an impressive training accuracy of 95.65%, showcasing its capability to learn from the training data effectively. With a validation accuracy of 92.88%, the model demonstrates good generalization to unseen data, making it a strong contender.
- **ResNet50**: ResNet50 attains an outstanding training accuracy of 99.45%, showcasing its ability to learn complex patterns from the data. The model also exhibits excellent generalization capabilities with a validation accuracy of 96.72%.
- **ResNet101**: ResNet101 achieves a high training accuracy of 98.12%, effectively capturing the features in the training data. The validation accuracy of 93.12% demonstrates satisfactory generalization, although slightly lower than ResNet50.
- **Proposed Model (VGG16 + ResNet50)**: The proposed model outperforms all other models with an outstanding training accuracy of 99.99%. It also demonstrates exceptional generalization capabilities, achieving a validation accuracy of 99.78%, making it the most promising choice for the task.
  Optimizer and Learning Rate: The paper employs the Adam optimizer with a learning rate of 0.001 for training the proposed model (VGG16 + ResNet50), which yields remarkable accuracy results.
- **Overall Analysis**: VGG19 suffers from overfitting, limiting its suitability for this task due to its low validation accuracy. Both ResNet models (ResNet50 and ResNet101) perform well with high accuracy

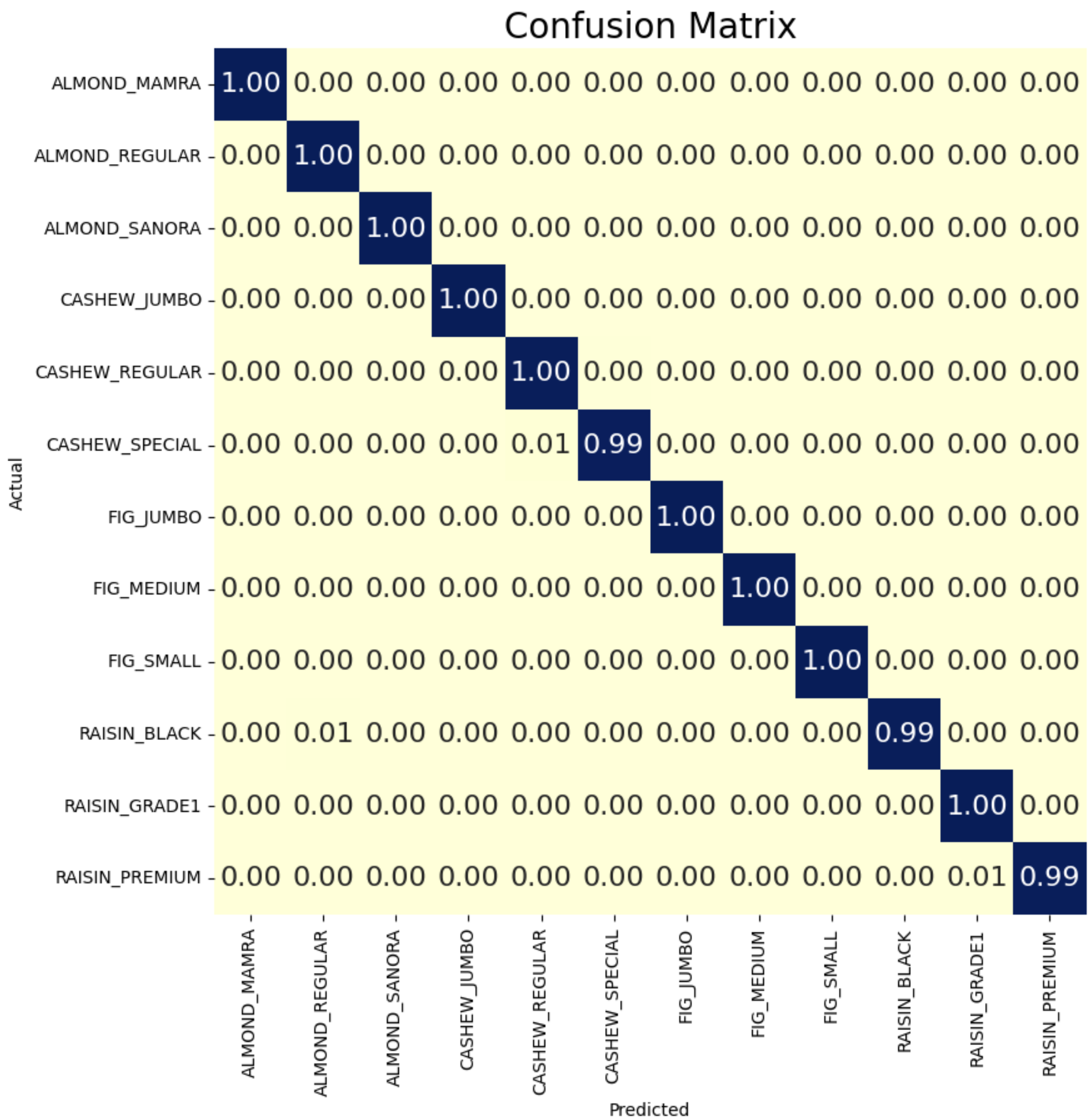

Figure 3. Confusion matrix, in order to improve classification algorithms, these metrics provide a comprehensive evaluation of the model's performance

on both training and validation data. VGG16 exhibits excellent generalization capabilities and competitive performance, positioning it as a strong candidate for the task. The proposed model, combining VGG16 and ResNet50, outperforms all others, achieving near-perfect accuracy on both training and validation sets.

Fig. 4, displays the precision and validation accuracy of the proposed system on both the training and validation sets. Accuracy measures how well the model classifies the images, while validation accuracy assesses its performance on new images.

Observations from Fig. 4:

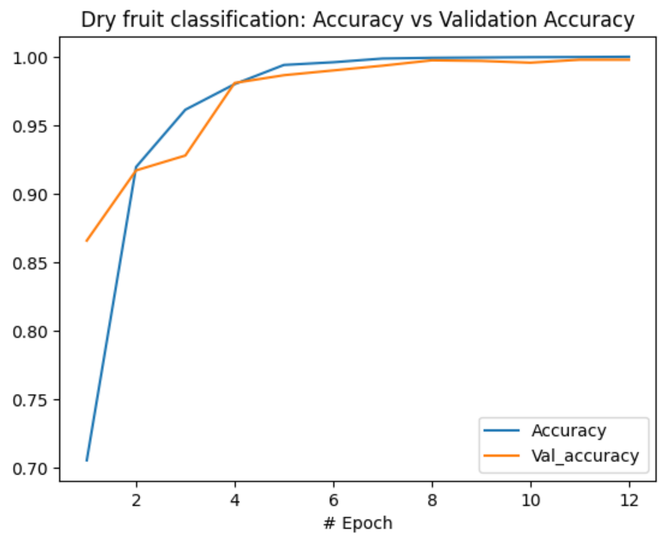

Figure 4. Visualising the Hybrid Method's Performance Using Accuracy

- The accuracy increases as the number of epochs increases, indicating effective image classification learning by the model.
- The validation accuracy also increases initially but stabilizes after a certain point, suggesting the model avoids overfitting the training data.
- The small difference between validation accuracy and accuracy indicates the model's ability to generalize well to new data without significant performance drops.

Overall, the plot's results indicate the proposed model is a strong choice for dry food item classification. It demonstrates successful learning and generalization capabilities, making it a reliable classifier. Fig. 5, displays the system losses (training and validation) of the proposed model. The loss represents how effectively the model fits the training data, while the validation loss evaluates its performance on unseen data.

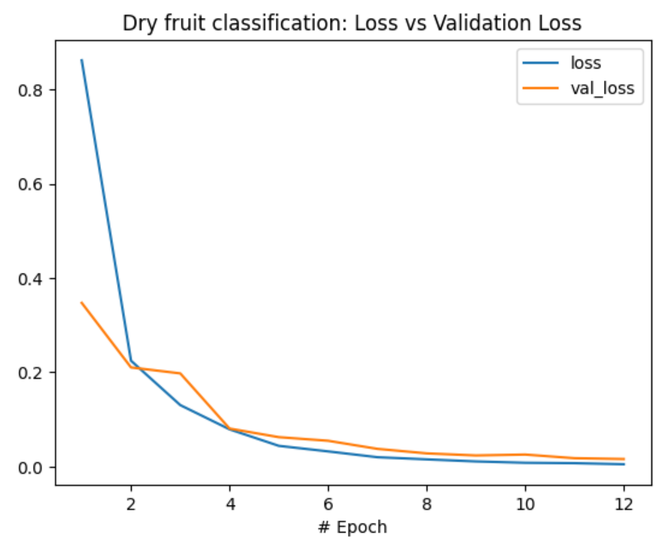

Figure 5. Loss curve for visualizing the Hybrid Method's Performance

Observations from Fig. 5:

- The loss decreases gradually with increasing epochs, indicating the model learns from the training data effectively.
- Similarly, the validation loss decreases initially but stabilizes after a certain point, suggesting the model avoids overfitting. Moreover, the small difference between the validation loss and the loss indicates that the proposed model generalizes well to new data, demonstrating its ability to learn the training data's features without overfitting.

Overall, the plot's results support the conclusion that the proposed model is well-suited for classifying dry food items. It exhibits strong learning capabilities from the training data and generalizes effectively to new, unseen data.

4.1.3. Comparison with Existing Works: In recent years, various techniques have been employed for accurate classification and analysis in different domains. Table 2 summarizes some of the notable references in this area along with the techniques they used and the achieved accuracy on training and validation datasets.

Table 2. Compare the effectiveness of our suggested model to the precision of other techniques and models.

Ref.	**Acc. (Train/Val)**	**Techniques**
Khan [11]	93.00% 95.40%	XGBoost, ADASYN
Nirere [12]	97.67% 96.66%	Hyperspectral imaging, GWO-LS-SVM
Kwon [13]	Varies	X-ray imaging, one-class classification
Monteiro [14]	N/A	Novel food classification
Prabowo [15]	N/A	Colorimeter, Arduino
He [16]	84.2% (Top 4)	Image classification, feature fusion
Steinkraus [17]	N/A	Nutritional fermentation benefits
Pan Gao [18]	>90%	Hyperspectral imaging, ML
Proposed Model	99.99% 99.78%	Hybrid Deep Transfer Learning

4.1.4. Error Analysis: The paper successfully explores diverse DL models for dry food item classification. The proposed model, a fusion of VGG16 and ResNet50, demonstrates outstanding accuracy and generalization, making it the optimal choice among the models studied. The use of the Adam optimizer with an appropriate learning rate further enhances the model's performance. The findings offer valuable insights into effectively categorizing dry food items, with potential practical applications in the food industry and related domains.

4.2. Discussion

The categorization of dry foods using a hybrid model that combines VGG16 and ResNet50 demonstrates an admirable method for resolving the difficulties involved in classifying various food categories. Multiple DL architectures used in a hybrid environment have been shown to improve the accuracy and robustness of classification tasks. Other models (VGG16, VGG19, ResNet50, and ResNet101) were unable to accomplish this.

The hybrid architecture's choice of VGG16 and ResNet50 as constituent models has produced a flexible framework for encoding complicated features at different levels of abstraction. Through this hybridization, the model is able to take advantage of the distinctive features of each design, producing a thorough comprehension of the subtleties of the dry food imagery. The hybrid model's high validation accuracy underlines the effectiveness of this approach. Furthermore, the use of this hybrid model could have important ramifications for real-world food industry applications, particularly for automating dry food classification procedures. The improved accuracy attained via the combined efforts of these DL architectures may help improve supply chain management and quality control in the field of food technology. Performance may be limited to certain image classifications, making it impossible to extrapolate to other datasets. To guarantee the accuracy and applicability of the model in real-world scenarios, it is crucial to keep in mind the restrictions mentioned. By addressing these constraints, future food classification research may become more thorough and significant.

5. Conclusion

In summary, this research addressed the challenge of classifying various types of dried foods using a hybrid deep-transfer learning approach. Our methodology combined the strengths of VGG16 and ResNet50 models, resulting in exceptional accuracy. Compared to other models, our approach achieved a validation accuracy of 99.78%, showcasing its potential for accurate dry food classification. This study contributes to both machine learning and food technology fields by introducing an effective method for automating dry food categorization. The practical implications are significant, potentially improving quality control and supply chain processes. While further diversification of the dataset and exploration of alternative techniques could enhance the approach, our research demonstrates the promise of hybrid deep transfer learning in addressing real-world challenges and advancing knowledge in the field.

Declaration of Competing Interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

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