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Deep Learning-Based Classification of Grains: A Comparative Study of MobileNetV2 and ResNet50 with Web Deployment

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Abstract: Classification of grain quality is essential to the agricultural and food processing industries; without this proper identification of the grain types and impurities, it may lead to potentially reduced standards and increased safety risks to consumers. In this project, such comparative analysis has been performed with respect to the two most popular deep learning models-MobileNetV2 and ResNet50-which are applied to grain images for classification. Both models were trained and tested using a custom dataset developed-by the use of various classes of grains-for accuracy, prediction confidence, and class-wise performance. Furthermore, the system will incorporate a user-friendly web interface developed using Streamlit, enabling uploading of grain images and classification results together with visualizations of model confidence. Results indicate the trade-off between lightweight efficiency in MobileNetV2 and rich deeper representation in ResNet50. This work would show the employability of deep learning models into accessible web applications for applied grain inspection tasks while imparting knowledge about the model selection for embedded or real-time scenarios.

Keywords: Grain Classification, Deep Learning, MobileNetV2, ResNet50, Streamlit, Image Recognition, Web-Based Deployment.

I. INTRODUCTION

Grain classification is a primary step in food quality assurance and agricultural commerce. Manual grain inspection is time-consuming, error-prone, and not scalable. Thanks to computer vision developments and deep learning, automatic classification based on images has presented itself as the best solution.

Two of the top convolutional neural network architectures are compared in this study: MobileNetV2 and ResNet50. Classifying grains using image data, these models are cloud-embedded through a Streamlit application for real-time classification processes, confidence visualizations, and model comparison facilities. It aims at evaluating the performance of each model with respect to accuracy, speed, and deployment readiness for agricultural or industrial contexts.

II. MOTIVATION

Manual grain sorting and quality grading are prone to inconsistencies and slow processing. There is a growing demand for intelligent systems that can automatically classify grain types to assist in packaging, sorting, and grading.

While deep learning offers high accuracy in image classification, many real-world systems are not easily deployable. Our motivation lies in combining the strength of deep learning with a real-time web interface to create a user-friendly, deployable solution for practical use. The project also seeks to explore the trade-off between lightweight models like MobileNetV2 and more complex architectures like ResNet50 in real-world scenarios.centralized systems is challenging, as voters may question the impartiality and security of the voting process, especially if the central authority is perceived as biased or corrupt. Furthermore, centralized systems often struggle to ensure voter anonymity and protect personal data, leading to privacy violations and undermining voter confidence in the election process.

III. LITERATURE SURVEY

[1] Enhancing Deep Convolutional Neural Network Models for Orange Quality Classification Using MobileNetV2 and Data Augmentation Techniques.

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This paper presents an enhanced orange quality classification model using MobileNetV2 combined with data augmentation strategies. The model addresses variations in lighting and background conditions and achieves improved accuracy through artificially expanded training data. The study demonstrates that MobileNetV2 is effective for agricultural quality inspection, especially when enhanced with data preprocessing techniques.

[2] Fruit Image Classification Model Based on MobileNetV2 with Deep Transfer Learning Technique.
The author introduces TL-MobileNetV2, a variation of MobileNetV2 enriched with a custom classification head and transfer learning. The model was trained on a 40-class fruit dataset and outperformed conventional CNN architectures, achieving 99% accuracy. The study highlights how lightweight architectures can deliver high performance in image classification tasks when fine-tuned and supported by data augmentation.

[3] Deep Learning Classification of Systemic Sclerosis Skin Using the MobileNetV2 Model.
This study explores the use of MobileNetV2 for medical image analysis, particularly in classifying systemic sclerosis (SSc) skin images. The model integrates MobileNetV2 with UNet and transfer learning techniques to classify normal, early, and late-stage SSc with high accuracy. The architecture was deployed on a standard laptop without GPU support, proving its practicality for low-resource clinical environments.

[4] Classification of Cicer arietinum Varieties Using MobileNetV2 and LSTM
This paper proposes a hybrid deep learning model that combines MobileNetV2 for extracting spatial features and LSTM for learning temporal patterns in chickpea (Cicer arietinum) variety classification. The integration of spatial and sequential data helps in achieving higher classification accuracy, making the approach suitable for applications where both texture and progression over sequences matter.

[5] Comparative Analysis of Texture Feature Extraction Techniques for Rice Grain Classification:
The study evaluates multiple texture-based feature extraction techniques, such as GLCM and GLRLM, for classifying eight rice grain varieties. The authors compare these methods against proposed texture features and demonstrate their effectiveness in differentiating grain types. The research underscores the continued relevance of classical texture analysis, especially in scenarios with limited access to deep learning infrastructure.

IV. PROPOSED SYSTEM

A. Dataset
The dataset comprises labeled images of 13 grain classes such as Bengal Gram, Urad Dal, Moong Dal, etc. Each class contains a balanced number of images captured under varying lighting and backgrounds.

B. Preprocessing
Images are resized to 224x224, normalized, and augmented using techniques like random flipping, zoom, and rotation to improve model generalization.

C. Model Architecture
- **ResNet50** is a 50-layer residual network known for high accuracy on image tasks.
- **MobileNetV2** is a light-weight CNN optimized for edge devices and fast inference.

Both models are fine-tuned using transfer learning with ImageNet weights. A softmax layer maps to 13 classes.

D. Streamlit Interface
A Streamlit-based web UI allows users to upload images, compare predictions from both models, view confidence scores, and monitor inference time.

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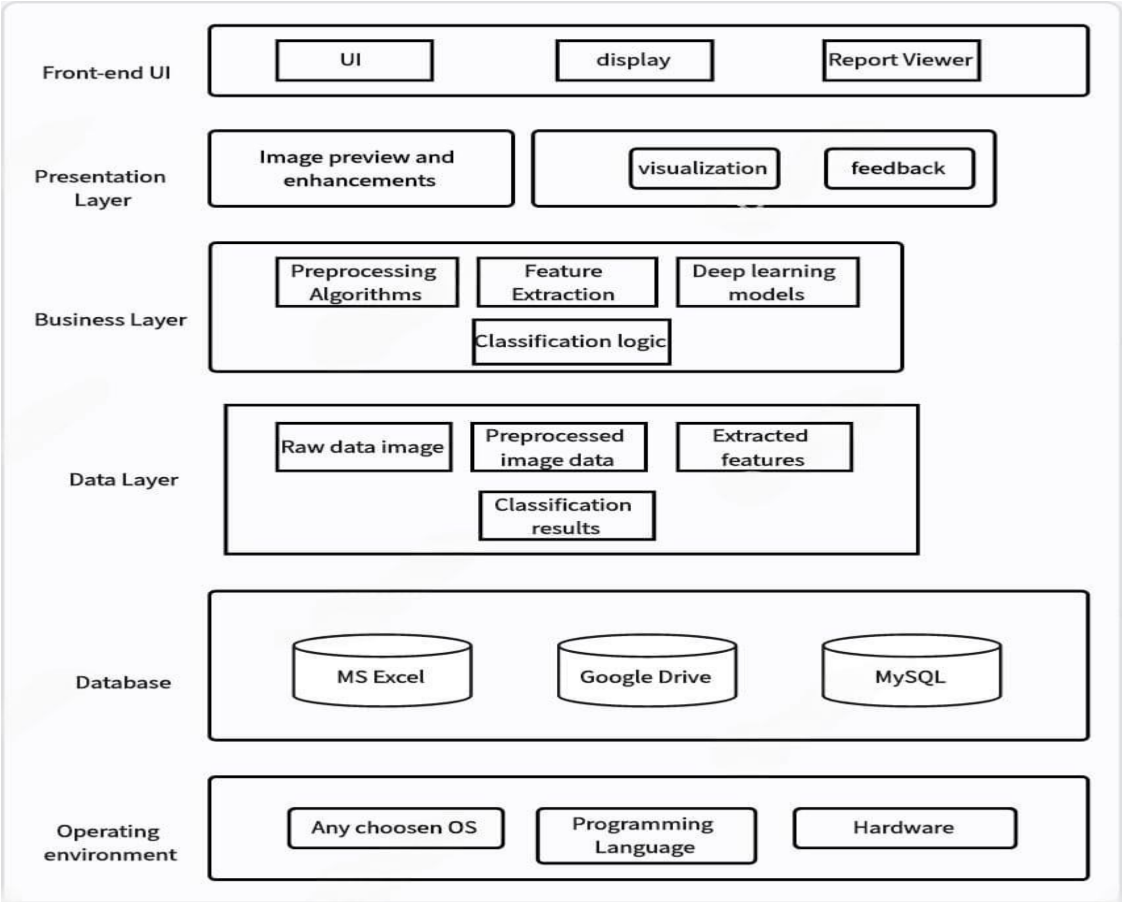

Fig 1: System Architecture

The proposed grain classification system consists of a multi-layer architecture that provides modularity, scalability, and ease of deployment. The Operating Environment is the lowest layer where the construct includes hardware and programming language (like Python). It is an operating system that can go on any flexible type of Windows, Linux, or macOS. At this layer, the basic infrastructure is made possible for running the application. The Database Layer puts persistence storage and access paths for data and results by making use of such platforms as MS Excel, Google Drive, or MySQL for storing grain images, features extracted from them, and classification outputs.

Above this is the Data Layer, which arranges handling data mobility through the whole system, managing raw input images and converting them to pre-processed image data while extracting important features and finally saving classification values for captioning. The Business Layer is where all the computation actions happen within the system, such functions as preprocessing algorithms, features extraction techniques, and the deep learning models (ResNet50 and MobileNetV2) act. It specifies the logic used for classification mapping the result from the model to a type of grain.

Presentation Layer is the one which will transform the data into different interpretable and visual formats where consists the modules for image preview and enhancement, graphical visualization of model confidence, and user feedback interfaces. At the very top level, the Front-End User Interface (UI), built upon Streamlit, brings an interactive web application to where the end-users are able to upload images, get predictions, display visual charts, and download classification reports all in one package. Such a layered design ensures component specification, but further makes an improvement in real-world agricultural deployment capacity, usability, and maintainability of the application.

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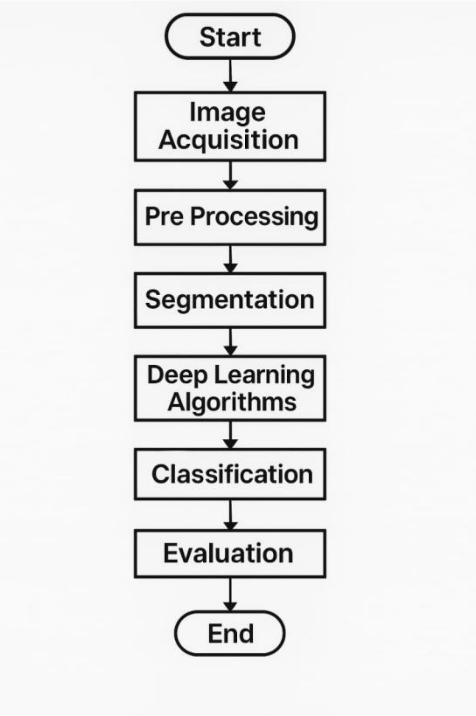

Fig 2: Flow chart

The workflow of the proposed grain classification system follows a systematic and modular approach, beginning with the **Image Acquisition** phase. In this step, high-quality images of various grain types are captured or collected from existing datasets. These images serve as the primary input for the system. The next stage is **Pre-processing**, where the images are resized, normalized, and enhanced to reduce noise and improve the consistency of data input. This step ensures that the deep learning models receive uniform and clean images for further analysis.

Following pre-processing, the system enters the **Segmentation** phase, where specific regions of interest are extracted, or background elements are removed if necessary. This focuses the model's attention on the grain features alone. The segmented images are then passed through the **Deep Learning Algorithms**, where feature extraction and learning take place using pre-trained convolutional neural networks such as ResNet50 and MobileNetV2. These models are fine-tuned to learn intricate patterns and textures specific to each grain class.

After feature learning, the system performs **Classification**, mapping each input image to a predicted grain class based on the model's confidence scores. Finally, the process concludes with the **Evaluation** phase, where the model's performance is assessed using metrics such as accuracy, confusion matrix, inference time, and confidence visualization. This evaluation helps in determining the most suitable model for real-time deployment. The process then ends, having successfully classified the input and provided interpretable results to the user.

V. RESULTS

Metric	**ResNet50**	**MobileNetV2**
Test Accuracy	97%	99%
Inference Time	~ 9445 ms	~7504 ms
Parameters	23M	3.4M
Top-1 Class Confidence	Moderate	High

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VI. CONCLUSION

This study demonstrates that deep learning models can effectively classify grains based on image data. While ResNet50 offers better accuracy, MobileNetV2 provides faster inference with less computational cost. The use of a Streamlit web app allows for practical deployment and easy usability. This comparative approach aids in selecting the right model based on context—ResNet50 for accuracy-critical applications and MobileNetV2 for real-time or resource-constrained scenarios. Future work includes impurity grading, multi-label classification, and integration with IoT-based grain sorting devices.

REFERENCES

[1].Enhancing Deep Convolutional Neural Network Models for Orange Quality Classification Using MobileNetV2 and Data Augmentation Techniques, Phan Thi Huong, Lam Thanh Hien, Nguyen Minh Son, Huynh Cao Tuan, Thanh Q. Nguyen, 2025

[2].Fruit Image Classification Model Based on MobileNetV2 with Deep Transfer Learning Technique, Yonis Gulzar, 2023

[3].Deep Learning Classification of Systemic Sclerosis Skin Using the MobileNetV2 Model, Metin Akay, Yong Du, Cheryl L. Sershen, Minghua Wu, Ting Y. Chen, Shervin Assassi, Chandra Mohan, Yasemin M. Akay, 2021

[4].Classification of Cicer arietinum Varieties Using MobileNetV2 and LSTM, Ali Yasar, Ibrahim Saritas, Hakan Korkmaz, 2023

[5].Comparative Analysis of Texture Feature Extraction Techniques for Rice Grain Classification, Kshetrimayum Robert Singh, Saurabh Chaudhury, 2020

BIOGRAPHY

Mr.Pradeep M, currently working as an Assistant Professor in the Department of Information Science and Engineering at SSIT College. I hold a Bachelor's degree in Engineering (B.E) and a Master's degree in Technology (M.Tech), and I am presently pursuing my Ph.D. My expertise lie in the areas of Java programming, Object-Oriented Programming (OOPs), and Database Management Systems (DBMS). With a strong foundation in both teaching and industry-oriented knowledge, I strive to bridge the gap between academic learning and practical application. I am passionate about guiding students, fostering innovation, and contributing to meaningful research in the field of Engineering.

Ms. Bhagyashree Badadal, I am Bhagyashree Badadal, an 8th-semester engineering student at Sri Siddhartha Institute of Technology, specializing in Information Science. Passionate about Java, I've built full stack applications and developed projects in IoT and data analysis. My curiosity in cybersecurity fuels my research on secure coding practices, threat detection, and data privacy. I'm a certified data analyst and a dedicated learner, eager to apply technology to solve real-world problems.

Ms.Javeriya Khanam A, I'm Javeriya Khanam A, a final-year Information Science engineering student at Sri Siddhartha Institute of Technology. My skills span Java, SQL, web technologies, and Unix, and I've built projects in web development, IoT, and data analysis. I'm deeply interested in application security and machine learning, aiming to create reliable, data-driven solutions. I actively pursue certifications and hands-on learning to grow as a developer.

Ms. Keerthana H N, pursuing my 8th semester in Information Science at Sri Siddhartha Institute of Technology. I have experience building dynamic web applications using HTML, CSS, JavaScript, and Java-based frameworks. I'm passionate about cybersecurity and have researched ways to secure web applications using blockchain and AI. I continue to expand my skill set through internships, certifications, and practical projects.

Ms. Nagarathna N, a final-year Information Science engineering student at Sri Siddhartha Institute of Technology. My skills span Java, SQL, web technologies, and Unix, and I've built projects in web development, IoT, and data analysis. I'm deeply interested in application security and machine learning, aiming to create reliable, data-driven solutions. I actively pursue certifications and hands-on learning to grow as a developer.