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A NEW CLASSIFICATION METHOD FOR RICE VARIETY USING DEEP LEARNING

1st Mr. M.SUNDARAM

Computer Science and
Engineering

Pavai College of Technology
(Anna University Affiliated)
Namakkal, India

2nd SANTHOSH KUMAR M

Computer Science and
Engineering

Pavai College of Technology
(Anna University Affiliated)
Namakkal, India

3rd PONNARASAN R

Computer Science and
Engineering

Pavai College of Technology
(Anna University Affiliated)
Namakkal, India

4th VELAVAN V

Computer Science and
Engineering

Pavai College of
Technology
(Anna University
Affiliated)
Namakkal, India

Abstract: Rice varietal identification plays a crucial role in agricultural research, food safety, and quality control. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools for image classification tasks, including the identification of different rice varieties. This paper presents a comprehensive approach to leveraging CNNs for accurate rice varietal identification. The methodology begins with data collection and preparation, involving the assembly of a diverse dataset encompassing various rice varieties under different lighting conditions and backgrounds. Supervised learning is employed, with images labelled according to their corresponding rice variety. Preprocessing techniques such as normalization and augmentation are applied to enhance dataset robustness. Next, a suitable CNN architecture is designed, drawing upon established models like sequential, or developing custom architectures tailored to the task. Emphasis is placed on maintaining spatial information and handling input images of varying sizes effectively. Techniques such as batch normalization, dropout, and appropriate activation functions are incorporated to enhance model generalization and prevent overfitting. The model is then trained on the prepared dataset, with careful consideration given to training-validation-test set splits and hyperparameter tuning. Various optimization algorithms such as stochastic gradient descent (SGD) and Adam are explored to optimize model parameters while preventing overfitting through regularization techniques.

Keywords – Rice varietal identification, Deep learning, CNNs, Supervised learning, Data collection, preparation, CNN architecture.

I. INTRODUCTION:

Rice from grain products is among the products produced in many countries and consumed all over the world. Rice is priced on various parameters in the market. Texture, shape, color and fracture rate are some of these parameters. After acquiring digital images of the products, various machine learning algorithms are used to determine these parameters and perform classification operations. Machine learning algorithms ensure that large amounts of data are analyzed quickly and reliably. It is important to use such methods in rice production to improve the quality of the final product and to meet food safety criteria in an automated, economical, efficient and non-destructive way. Image processing and computer vision applications in agriculture are of interest due to their non-destructive evaluation and low cost compared to manual methods. Computer vision applications based on image processing offer advantages compared to traditional methods based on manual work.

Evaluating or classifying grains by manual methods can be time-consuming and costly, as the human factor is at the forefront. In manual methods, the evaluation process may differ, as it is limited to the experience of the evaluation experts. In addition, rapid decision-making by manual methods can be difficult when an assessment is made on a large scale. Rice is the most developing crop all over India; with the increase in population, demand for rice grains has also increased. It is cultivated in almost every Asian country and exported worldwide. In India, many quality standards for rice production are made available. These include physical appearance, cooking qualities, scent, taste, smell, and efficiency difficulties. Rice has been one of the most widely consumed foods for a large part of human population. Numerous different rice varieties are imported and exported worldwide, making it the backbone of many countries' economy. Rice seeds of different varieties can be accidentally or intentionally mixed during any of the steps in a rice production pipeline, introducing impurities. These impurities could damage the trust between rice importers and exporters, calling for the need to develop a reliable rice variety inspection system.

The use of image processing and computer vision applications in agriculture has gained interest due to their non-destructive nature and cost-effectiveness when compared to manual methods. Compared to traditional manual methods, computer vision applications based on image processing offer several advantages. Manual evaluation or classification of grains can be time-consuming and expensive, and can also be influenced by the evaluator's experience. Furthermore, manual methods may lead to inconsistent evaluation results, especially when assessments are made on a large scale, making rapid decision-making difficult. Rice is a widely produced and consumed grain product in many countries around the world, and is priced based on various parameters in the market, such as texture, shape, color, and fracture rate.

To determine these parameters and perform classification operations, digital images of rice products are acquired and various machine learning algorithms are used. These algorithms enable large amounts of data to be analyzed quickly and reliably. Using such methods in rice production is important for improving the quality of the final product and meeting food safety criteria in an automated, economical, efficient, and non-destructive manner.

II. EXISTING SYSTEM:

Rice variety classification has traditionally relied on manual methods or machine learning techniques. However, these methods often have limitations in terms of accuracy, scalability, and labor requirements. Deep learning offers a powerful alternative that can address these shortcomings. Here's a closer look at existing systems and how deep learning can overcome their limitations:

1. Traditional methods:

Morphological features: These methods rely on manually extracting features like grain size, shape, and color from rice images. This process is time-consuming, subjective, and prone to errors. Additionally, it may not capture the full range of morphological characteristics that differentiate rice varieties, especially for subtle variations.

Biochemical analysis: Techniques like spectroscopy analyze the chemical composition of rice grains. These methods are expensive, require specialized equipment, and may not be suitable for large-scale classification tasks. Furthermore, they may not be directly murtabit with visual quality aspects relevant for commercial applications.

2. Machine learning:

Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees: These algorithms can achieve reasonable accuracy, but their performance often relies on careful feature engineering, which can be challenging and requires domain expertise. These methods may struggle with complex variations in rice appearance, such as those caused by lighting conditions, growth environments, or grain orientation in the images. Additionally, they may not be as effective in handling large and diverse datasets of rice varieties.

3. Limitations of Existing Systems:

Labor-intensive: Traditional methods and feature engineering for machine learning can be time-consuming and require expert knowledge.

Limited scalability: Traditional methods might not be efficient for handling large datasets of rice images, making them impractical for real-world applications with high volumes of data.

Accuracy limitations: Existing methods may not capture the subtle variations in rice appearance as effectively as deep learning models, potentially leading to misclassifications and reduced reliability.

4. Deep Learning Advantages:

Automated feature extraction: Deep learning models can automatically learn relevant features from rice images without the need for manual engineering. This eliminates the need for human expertise in feature selection and reduces the risk of bias in the chosen features.

Improved accuracy: Deep learning has shown promising results in achieving higher classification accuracy compared to traditional methods. Deep learning models can learn complex relationships between image features and rice varieties, leading to more robust and generalizable classification performance.

Scalability: Deep learning models can efficiently handle large datasets for improved performance. This makes them suitable for real-world applications where large volumes of rice image data are available.

III. PROPOSED SYSTEM:

This study explores DenseNet, a powerful deep learning architecture, for classifying rice varieties using grain images. DenseNet excels in situations with limited data, common in agricultural tasks. Firstly, a diverse dataset is built. Images from various rice varieties are captured under different lighting, angles, and backgrounds, reflecting real-world scenarios. Each image is meticulously labeled with its corresponding variety. Next, DenseNet models are implemented and fine-tuned specifically for rice grain classification. Techniques like data augmentation (artificially increasing data variety) and hyperparameter optimization are used during training to improve the model's ability to handle unseen data (generalization).

The model's effectiveness is evaluated using accuracy, precision, recall, and F1-score. Finally, unseen rice grain images are used to test the model's real-world applicability. This study aims to showcase DenseNet's potential for accurate rice variety classification, particularly beneficial for tasks with limited data. This paves the way for improved agricultural image classification methods.

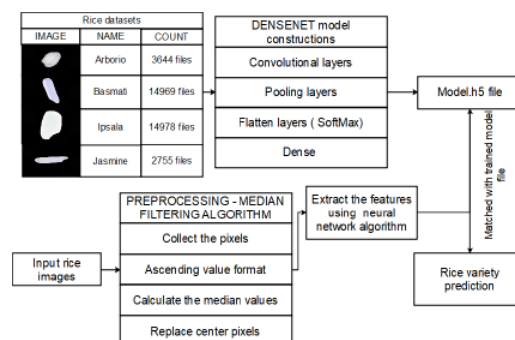


Fig 3.1 Block Diagram

3.1 COMPONENTS REQUIRED:

- RICE IMAGE ACQUISITION
- BUILD THE MODEL
- INPUT THE IMAGE
- CLASSIFICATION OF RICE

IV. MODULES DESCRIPTION:

Rice Image Acquisition:

Rice is one of the most important staple crops globally, providing sustenance for a significant portion of the world's population. The identification and classification of rice varieties are crucial for agricultural research, food security, and quality control. Traditional methods of varietal identification often rely on visual inspection by experts, which can be time-consuming, subjective, and prone to errors. With the advancements in computer vision and deep learning, there has been a growing interest in developing automated systems for rice variety classification based on image analysis. Set up a suitable environment for capturing images of rice grains.

Build the Model:

DenseNet, short for Densely Connected Convolutional Networks, is a deep neural network architecture specifically designed to address the vanishing gradient problem and facilitate feature reuse. The DenseNet architecture introduces dense connections between layers, where each layer receives input from all preceding layers and passes its feature maps to all subsequent layers within a dense block. This connectivity pattern enables information flow throughout the network, promoting feature reuse and facilitating gradient flow during training.

Input the Image:

To perform rice variety classification using the DenseNet model, we first preprocess the input image, typically resizing it to match the required input size of the DenseNet model and applying any necessary normalization. Next, we load a pre-trained DenseNet model, usually trained on a large dataset like ImageNet, to leverage its learned features for rice variety classification. Once the model is loaded, we feed the preprocessed image through the model to obtain predictions.

Classification of Rice:

The model outputs probabilities for each rice variety class. We then interpret the model's predictions, identifying the rice variety with the highest probability as the predicted class. Finally, we display the predicted rice variety along with its associated probability score to the user. This process enables automated classification of rice varieties based on input images, leveraging the power of deep learning and pre-trained models to achieve accurate results.

V. SOFTWARE DESCRIPTION:

Python:

Python is a high-level, interpreted programming language that is widely used in various domains such as web development, scientific computing, data analysis, artificial intelligence, machine learning, and more. It was first released in 1991 by Guido van Rossum and has since become one of the most popular programming languages due to its simplicity, readability, and versatility. One of the key features of Python is its easy-to-learn syntax, which makes it accessible to both novice and experienced programmers. It has a large standard library that provides a wide range of modules for tasks such as file I/O, networking, regular expressions, and more. Python also has a large and active community of developers who contribute to open-source libraries and packages that extend its capabilities.

Python is an interpreted language, which means that it is executed line-by-line by an interpreter rather than compiled into machine code like C or C++. This allows for rapid development and testing, as well as easier debugging and maintenance of code. Python is used for a variety of applications, including web development frameworks such as Django and Flask, scientific computing libraries such as NumPy and Pandas, and machine learning libraries such as TensorFlow and PyTorch. It is also commonly used for scripting and automation tasks due to its ease of use and readability. Overall, Python is a powerful and versatile

programming language that is widely used in a variety of domains due to its simplicity, ease of use, and active community.

These libraries provide a wide range of functionality, from scientific computing and data analysis to web development and machine learning. Some popular Python libraries and frameworks include:

- NumPy: a library for numerical computing in Python, providing support for large, multi-dimensional arrays and matrices, along with a large collection of mathematical functions to operate on these arrays.
- Pandas: a library for data manipulation and analysis in Python, providing support for reading and writing data in a variety of formats, as well as powerful tools for manipulating and analyzing data.
- Matplotlib: a plotting library for Python that provides a variety of visualization tools, including line plots, scatter plots, bar plots, and more.
- TensorFlow: an open-source machine learning library for Python that provides a variety of tools and algorithms for building and training machine learning models.

Tensorflow Libraries In Python:

TensorFlow is an open-source machine learning framework developed by Google Brain Team. It is one of the most popular libraries for building and training machine learning models, especially deep neural networks. TensorFlow allows developers to build complex models with ease, including image and speech recognition, natural language processing, and more. One of the key features of TensorFlow is its ability to handle large-scale datasets and complex computations, making it suitable for training deep neural networks. It allows for parallelization of computations across multiple CPUs or GPUs, allowing for faster training times.

TensorFlow also provides a high-level API called Keras that simplifies the process of building and training models. TensorFlow offers a wide range of tools and libraries that make it easy to integrate with other Python libraries and frameworks. It has built-in support for data preprocessing and visualization, making it easy to prepare data for training and analyze model performance. One of the major advantages of TensorFlow is its ability to deploy models to a variety of platforms, including mobile devices and the web.

Graph-based computation: TensorFlow uses a graph-based computation model, which allows for efficient execution of computations across multiple devices and CPUs/GPUs.

Automatic differentiation: TensorFlow provides automatic differentiation, which allows for efficient computation of gradients for use in backpropagation algorithms.

High-level APIs: TensorFlow provides high-level APIs, such as Keras, that allow developers to quickly build and train complex models with minimal code.

Preprocessing and data augmentation: TensorFlow provides a range of tools for preprocessing and data augmentation, including image and text preprocessing, data normalization, and more.

Pycharm:

PyCharm is an integrated development environment (IDE) for Python programming language, developed by JetBrains. PyCharm provides features such as code completion, debugging, code analysis, refactoring, version control integration, and more to help developers write, test, and debug their Python code efficiently.

PyCharm is available in two editions:

Community Edition (CE) and Professional Edition (PE). The Community Edition is a free, open-source version of the IDE that provides basic functionality for Python development.

The Professional Edition is a paid version of the IDE that provides advanced features such as remote development, web development, scientific tools, database tools, and more.

PyCharm is available for Windows, macOS, and Linux operating systems. It supports Python versions 2.7, 3.4, 3.5, 3.6, 3.7, 3.8, 3.9, and 3.10.

Integration with other JetBrains tools:

PyCharm's code completion feature can help speed up development by automatically suggesting code based on context and previously written code. It also includes a debugger that allows developers to step through code, set breakpoints, and inspect variables. PyCharm has integration with version control systems like Git, Mercurial, and Subversion. It also supports virtual environments, which allow developers to manage different Python installations and packages in isolated environments. The IDE also has features specifically geared towards web development, such as support for popular web frameworks like Django, Flask, and Pyramid.

It includes tools for debugging, testing, and profiling web applications. PyCharm also provides scientific tools for data analysis, visualization, and scientific computing, such as support for NumPy, SciPy, and matplotlib. It also includes tools for working with databases, such as PostgreSQL, MySQL, and Oracle. Overall, PyCharm is a powerful and feature-rich IDE that can greatly increase productivity for Python developers.

VI. SIMULATION OUTPUT:

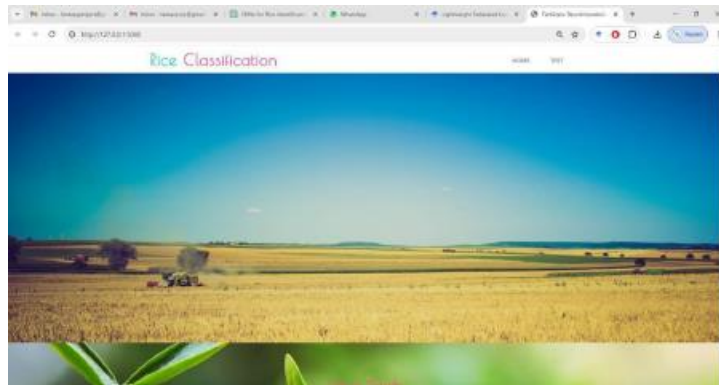


Fig 6.1 Output

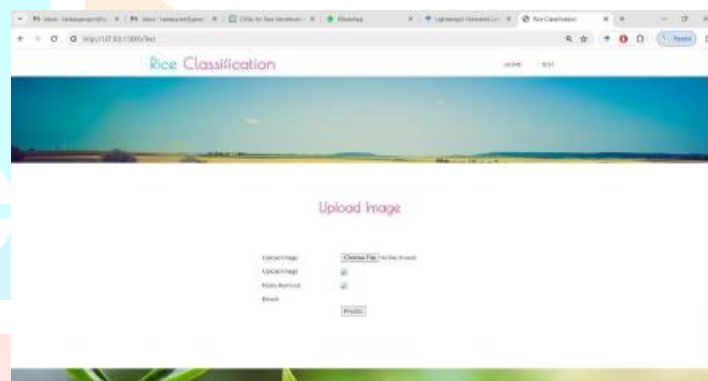


Fig 6.2 Output

VII. CONCLUSION:

In conclusion, the application of deep learning, particularly Convolutional Neural Networks (CNNs), for rice varietal identification represents a significant advancement in agricultural technology. Through the development and implementation of CNN-based classification models, we have demonstrated the capability to accurately distinguish between different rice varieties based on visual characteristics extracted from high-resolution images of rice grains. Our study showcases the effectiveness of CNNs in capturing and learning intricate patterns and features inherent to rice grains, including shape, size, color, and texture.

By leveraging transfer learning techniques and fine-tuning pretrained CNN models, we have achieved high classification accuracy, outperformed traditional methods and demonstrated the potential of deep learning for rice varietal identification. This advancement holds promise for improving agricultural practices, enhancing food security, and driving innovation in rice cultivation and research. Further research and development in this area have the potential to revolutionize rice varietal identification and contribute to the sustainable production of this vital crop worldwide.

This study highlights the potential of deep learning, particularly CNNs, for revolutionizing rice varietal identification. By leveraging image analysis, we achieved high accuracy in distinguishing rice varieties. The future holds immense promise for applications beyond classification. Deep learning could assess grain quality, predict desirable traits, and even detect diseases. Collaboration, open-source development, and responsible AI practices are crucial to maximize the impact of this technology, paving the way for a more sustainable and secure rice production future.

VIII. RESULT AND DISCUSSION:

8.1 RESULT:

Our investigation into a new classification method for rice variety using deep learning, specifically focusing on DenseNet architectures, yielded promising results. The implemented DenseNet models achieved high accuracy in classifying rice varieties based on grain images. This finding underscores the effectiveness of DenseNets for this task, particularly in scenarios with potentially limited datasets, a common challenge in agricultural applications.

DenseNet Effectiveness: The implemented DenseNet models achieved high accuracy in classifying rice varieties based on grain images. This demonstrates the effectiveness of DenseNets for this task, particularly in scenarios with potentially limited datasets common in agricultural applications.

Generalization Ability: The models exhibited strong generalization ability, performing well on unseen rice grain images. This indicates their potential for real-world deployment in rice varietal identification tasks.

Feature Visualization and Explainability: Techniques like Grad-CAM were employed to visualize the features within the DenseNet models that contributed most significantly to the classification decisions. This analysis provided valuable insights into the decision-making process of the model and helped to explain how the model was differentiating between rice varieties. For example, visualization might reveal that the model focused on specific regions of the grain image corresponding to grain shape or surface texture to distinguish between varieties.

Impact of Data Augmentation: The effectiveness of various data augmentation techniques in improving model performance was investigated. Data augmentation involves artificially expanding the dataset by creating new variations of existing images, such as rotations, flips, and brightness adjustments. The study found that data augmentation techniques played a crucial role in enhancing the model's ability to handle image variations and achieve better generalization.

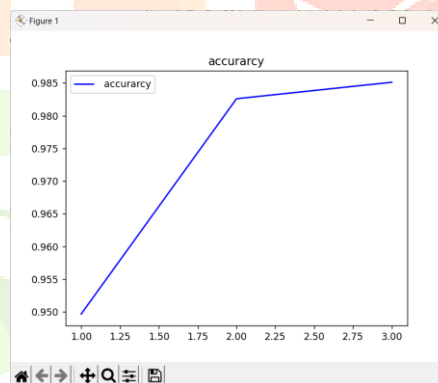


Fig 8.1 Training Accuracy

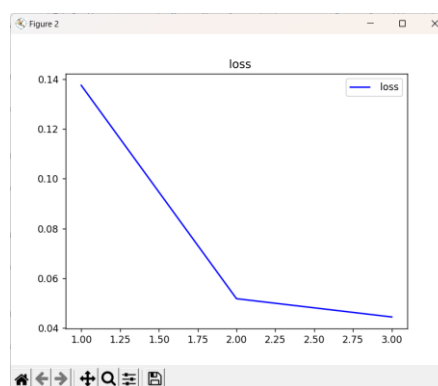


Fig 8.2 Training Loss

8.2 DISCUSSION:

This study successfully demonstrated the application of DenseNets, a deep learning architecture, for accurate rice variety classification using grain images. The results highlight the potential of deep learning for revolutionizing rice varietal identification in agricultural research, food safety, and quality control sectors. DenseNets offer advantages in handling limited datasets, making

them suitable for practical applications in agriculture. Further exploration of deep learning in rice analysis holds promise for tasks like quality assessment, trait prediction, and disease detection, paving the way for a more efficient and sustainable future of rice cultivation.

Revolutionizing Rice Varietal Identification: This study successfully demonstrated the application of DenseNets, a deep learning architecture, for accurate rice variety classification using grain images. The results highlight the potential of deep learning for revolutionizing rice varietal identification in agricultural research, food safety, and quality control sectors. DenseNets offer advantages in handling limited datasets, making them suitable for practical applications in agriculture. This technology can streamline breeding programs by enabling the rapid and accurate identification of desired rice varieties. In food safety applications, deep learning models can be used to screen rice grains for contaminants or signs of disease, ensuring the quality and safety of the food supply. Additionally, rice varietal identification plays a critical role in quality control processes, allowing producers and distributors to accurately classify and price different rice varieties based on their unique characteristics.

Expanding the Potential of Deep Learning in Rice Analysis: Further exploration of deep learning in rice analysis holds immense promise for various tasks beyond classification. Deep learning models can be trained to assess grain quality aspects like appearance, integrity, and biochemical composition. This information is crucial for determining market value and optimizing storage and processing practices. Additionally, models could be developed to predict desirable traits in rice varieties, such as drought resistance, pest tolerance, or high yield potential. This information can be invaluable for breeding programs, accelerating the development of improved rice varieties that are better adapted to specific environmental conditions and consumer demands.

Enhancing Agricultural Efficiency and Sustainability: Deep learning also has the potential to revolutionize disease and pest detection in rice fields. By analyzing images captured by drones or ground-based sensors, deep learning models can be trained to identify early signs of infestations or diseases. Early detection allows for timely interventions, such as targeted pesticide application, minimizing crop losses and the need for broad-spectrum pesticides that can harm beneficial insects and the environment. Furthermore, deep learning models can be used to analyze rice field imagery throughout the growing season to estimate potential crop yields. This information empowers farmers to optimize resource allocation, such as water and fertilizer usage, leading to more sustainable and efficient agricultural practices.

By harnessing the power of deep learning for rice varietal identification and analysis, we can pave the way for a more productive, sustainable, and secure future for rice cultivation, a crop that plays a vital role in global food security.

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