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RESEARCH ARTICLE

# Image-based identification of onion varieties using deep learning techniques

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## Abstract
Onion is a crop of immense economic and dietary importance, widely cultivated and traded globally. Accurate identification of onion varieties is critical for pricing, quality assurance, traceability, and consumer preference, yet remains challenging due to high morphological similarity across cultivars. This study is the first reported attempt to classify Indian onion varieties using deep learning applied to bulb images. We evaluated the performance of four pre-trained convolutional neural networks, DenseNet121, InceptionV3, MobileNetV2 and Xception, on a curated image dataset of 10 popular onion varieties. The result showed that DenseNet121 outperformed all models, achieving the highest precision (95.76%), recall (94.92%), F1 score (94.82%) and the lowest mean squared error of 0.94, demonstrating exceptional reliability and accuracy. Its dense connectivity architecture effectively captured subtle features, making it the most suitable for practical applications. InceptionV3 and MobileNetV2 also showed competitive results, with MobileNetV2 offering computational efficiency but facing challenges with certain misclassifications. Xception, despite its efficiency, had the lowest performance metrics, with precision and recall of 91.04% and 88.14%, respectively, and significant misclassification issues. These findings highlight the potential of DenseNet121 for automated onion variety identification and its superiority in addressing the intricate variability within agricultural datasets. These findings demonstrate the potential of deep learning for automating onion variety identification and supporting sorting, grading, and seed chain verification systems. Future work should extend to broader varietal coverage and seasonal datasets for real-world applications.

**Keywords:** Onion variety identification, Deep learning, CNN's, Training, Hyperparameters.

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## Introduction

Onion (*Allium cepa* L.) is a commercially valuable vegetable condiment of immense economic, medicinal and dietary importance, cultivated on almost every continent and used in every household food preparation throughout the year. It is a high-value crop, holding a dominant position in the international market among agricultural commodities (Setiya and Muthuselvan, 2018). Globally, it is cultivated second to tomatoes in an area of 5.84 million hectares with a total production of 111 million tons (FAOSTAT, 2023). The major onion-producing countries are India, China, Egypt, the USA, Bangladesh, Turkiye, Pakistan, Indonesia, Iran, and Algeria, accounting for 68% of the world's production. China has been the largest producer of onions globally. However, according to the latest reports, India has recently overtaken China as the largest onion producer with the production of 30.21 million tons in an area of 1.74 million hectares. Recently, India has become one of the largest exporters (2 million tons) of onions globally, surpassing the Netherlands, contributing significantly to both domestic and international market production (FAOSTAT, 2023; Ministry of Commerce and Industry, Government of India, 2023-24). This is possible due to the continuous development of new high-yielding varieties along with cultivation practices. This has led to rapid globalization of the onion seed and bulb market, and competition for seed and bulb trade has been steadily rising, along with increasingly strict quality standards (Dias, 2010; Dias and Ortiz, 2021). As a result, a wide range of new onion varieties are developed and introduced for cultivation each year, ensuring adaptability to market demands and diverse growing conditions. In the case of the onion, the bulb is a propagating material as well as a part of economic use. Therefore, it is the subject of attention throughout its supply chain. From the selection of varieties by producers to the choices made by consumers, precise identification of varieties is of vital importance.

Traditionally, onion varieties are identified through manual experience and visual observation of morphological traits. Varieties can be differentiated based on morphological, biochemical and molecular traits (Korir et al., 2013). Morphological observations are based on a set of key traits under DUS testing (Distinctness, Uniformity, Stability) such as leaf colour, flower colour, plant height, fruit colour, shape, etc. (Barthélémy and Caraglio, 2007; Gupta and Mahajan, 2018; Gupta et al., 2022; Sunpapao et al., 2022). Though easy and effective, morphological traits are subjected to environmental influence (Ahmed et al., 2013). Biochemical traits, such as protein content, pungency, and oil content, can be used as markers to identify varieties, but they are not feasible, as their composition can vary depending on growing conditions (Marone et al., 2022). Other methods, such as molecular detection, are highly effective for identifying onion varieties using markers like randomly amplified polymorphic DNA (RAPD), simple sequence repeats (SSR), amplified fragment length polymorphism (AFLP), and single nucleotide polymorphism (SNP) (Kim et al., 2003; Mahajan et al., 2009; Tedeschi et al., 2014; Almontero and Espino, 2016). This method provides high reliability, accuracy, and consistency in distinguishing varieties, as they are based on genetic information, which remains stable regardless of environmental influences. However, these methods are also costly and complex. They require specialized laboratory equipment and expertise to perform, limiting their accessibility for routine or market-based variety identification (Hussain and Nisar, 2020).

Recently, computer vision and machine learning have emerged as powerful tools for plant variety identification, revolutionizing traditional methods that rely on manual observation and expertise (Li et al., 2020; Ghazal et al., 2024). Deep learning is becoming popular for image recognition and classification tasks of fruits and vegetables (Srivalli and Geetha, 2019). Convolutional neural networks (CNNs) based on deep learning allow researchers to automatically extract, process, and analyze features from plant images, leading to more accurate and efficient classification of different plant varieties. They are fast, efficient, and robust, reducing the impact of environmental factors that typically affect traditional methods. CNN models can handle large datasets, work in real-time applications, and improve over time as more data is provided for food and agricultural tasks (Dhanya et al., 2022). Although initial setup costs can be high, they become cost-effective and adaptable for large-scale use in agriculture, breeding, and quality control, offering a cutting-edge solution for plant identification (Kamilaris and Prenafeta, 2018). Deep learning in agriculture serves two main purposes: first, it helps with identifying plant varieties and performing high-throughput phenotyping (Ubbens and Stavness, 2018). Second, it is used for monitoring plant health and identifying diseases (Brahimi et al., 2017; Ferentinos, 2018). Many studies have been carried out to identify varieties of pistachio (Heidary et al., 2021), wheat (Laabassi et al., 2021), chickpea (Taheri et al., 2021), mango (Abou et al., 2024) and apples (Taner et al., 2024) through the use of machine learning.

In onion, a combination of fluorescence spectroscopic data and machine learning algorithms of LMT (Logistic Model Tree), Multilayer Perceptron, Naive Bayes, Logit Boost, and LWL (Locally Weighted Learning) differentiated two varieties of red onion with 100% accuracy was found effective (Sabanci et al., 2022). More recent algorithms, such as transfer learning, have the potential to achieve better performance due to their ability to automatically learn complex patterns and relationships in data. While the VGG19 convolutional neural network (CNN) architecture has been applied to classify broad categories such as red onion, shallots, sweet onion, and yellow onion with 95% accuracy (Ronquillo et al., 2023), CNNs have been used not only to distinguish between red and white onion bulbs but also to differentiate good bulbs from damaged bulbs (Waghmare et al., 2023; Pawar and Deshpande, 2024). Studies have been extensively employed to identify various foliar and storage diseases in onions (Kim et al., 2020; Zaki et al., 2021; Vikhe et al., 2024; Kaur et al., 2024; Asnakew et al., 2025; Raj et alw., 2025). However, despite these advances, very few or no studies (Puspadhani et al., 2021; Rybacki et al., 2024) have specifically focused on the identification of onion varieties at the cultivar level based on bulb images.

Bulb-based varietal identification in onions is particularly challenging due to several factors, especially in India, where a wide range of dark to light red, yellow and white onion varieties are cultivated, showing significant variation in shape, size, and colour. Identifying onion varieties accurately in markets is crucial for pricing, quality assurance, and consumer preference. Traders and consumers may recognize certain varieties based on flavour preferences or shelf life. For instance, Nashik onions from India are known for their distinct pungency, but these preferences are often based on experience rather than clear identification systems. To address this, a collaborative program between ICAR-DOGR, Pune and TIH-IoT, IIT, Bombay was initiated to identify varieties dominant in the Indian market and seed chain using deep learning techniques. Therefore, 10 varieties of onion were selected to perform the classification task in this study.

## Material and Methods

### *Varietal dataset*

Ten onion varieties developed and available for cultivation in India were selected based on their market dominance and the availability of these varieties in the seed chain (Table 1). These varieties were sown in flat beds of size 3×2 m, with 15×10 cm row-row and plant-plant spacing at the research farm (18° 32′ N, 73° 51′ E) of ICAR-Directorate of Onion and Garlic Research (DOGR), Pune, during *rabi* 2023-2024. The mature bulbs harvested in April-May 2024 were brought to the storage facilities after curing. Bulbs' best-representing variety was selected for photographs. The data analysis related to deep learning was performed at the Agriculture Knowledge Management Unit (AKMU), ICAR-DOGR, Pune.

### *Data acquisition and dataset construction*

The bulbs were photographed using high quality camera with 18.5 megapixels (Canon EOS 700D), against a black background to reduce the interference of external environmental factors on model learning. Onion bulbs show natural variability in terms of size, shape, colour, thickness of neck, root disc position and presence of veins appearance on scaly bulb. The images were taken with the precision of 5184 * 3456 pixels per inch (ppi) to best represent the six DUS traits, which are bulb colour, bulb shape, neck thickness, position of root disc, bulb height (cm) and bulb diameter (cm) belonging to bulb characters that are visible in images. This variability provides valuable features that can enhance deep learning models for variety identification.

**Table 1:** Onion varietal dataset used in this study

| *S. No.* | *Variety/Cultivar* | *Source* | *Number of images* |
|---|---|---|---|
| 1 | Agrifound Dark Red | NHRDF, Nashik | 50 |
| 2 | Arka Pitamber | ICAR-IIHR, Bengaluru | 50 |
| 3 | Bhima Dark Red | ICAR-DOGR, Pune | 50 |
| 4 | Bhima Kiran | ICAR-DOGR, Pune | 50 |
| 5 | Bhima Light Red | ICAR-DOGR, Pune | 50 |
| 6 | Bhima Shubhra | ICAR-DOGR, Pune | 50 |
| 7 | Bhima Shweta | ICAR-DOGR, Pune | 45 |
| 8 | Pillipatii Junagadh | JAU, Junagadh | 50 |
| 9 | PKV White | PDKV, Akola | 50 |
| 10 | Sukhasagar | Local landrace | 50 |
| | | Total | 495 |

Each characteristic provides unique visual information. By training on images that capture these features, the model can learn patterns associated with specific varieties, making it easier to recognize and classify them based on subtle visual cues. The model can learn fine-grained differences, such as slight variations in neck thickness or veins patterns, which might be characteristic of certain varieties. These fine distinctions can be difficult for humans to discern, but are detectable by deep learning algorithms. To capture these best DUS traits, photos were captured in 2 to 3 angles and with lighting variations to assess the model's robustness to lighting variations. To ensure the accuracy and consistency of our data collection, we avoided images that are too blurry, pixelated, or have too much noise. Single bulb centered, entirely visible from all edges, placement was ensured (Fig. 1). Illustration in Fig. 2 gives a visual overview of these 10 varieties. The image dataset consisted total of 495 images.

### *Pre-processing and labelling*

In our study, we used the Roboflow platform for pre-processing and labelling images. Roboflow is a popular platform that simplifies image annotation, data pre-processing, and dataset management, particularly for computer vision projects. It's well-suited for tasks like object detection, image segmentation and classification (Prakash, 2024). Roboflow provides an intuitive interface for labelling, allowing one to mark specific regions or classify entire images. For object detection, it offers bounding boxes drawing around regions of interest, such as distinct onion types. It offers a range of pre-processing tools to prepare images for machine-learning models. The initial dataset was subjected to data processing and augmentation in Roboflow. First augmentation involved resizing of images to 224 * 224, stretching vertically and horizontally, horizontal and vertical flip, 90° upside down rotation and noise up to 0.1% of pixels on 495 labelled images (Fig. 2). Data augmentation expands the dataset by creating varied versions of training samples (e.g., through rotations, flips, and noise). This helps deep learning models generalize better, become more

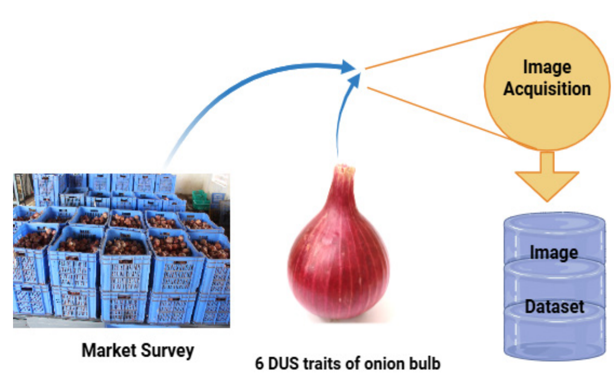


**Fig. 1:** Workflow for construction of the onion varietal image dataset

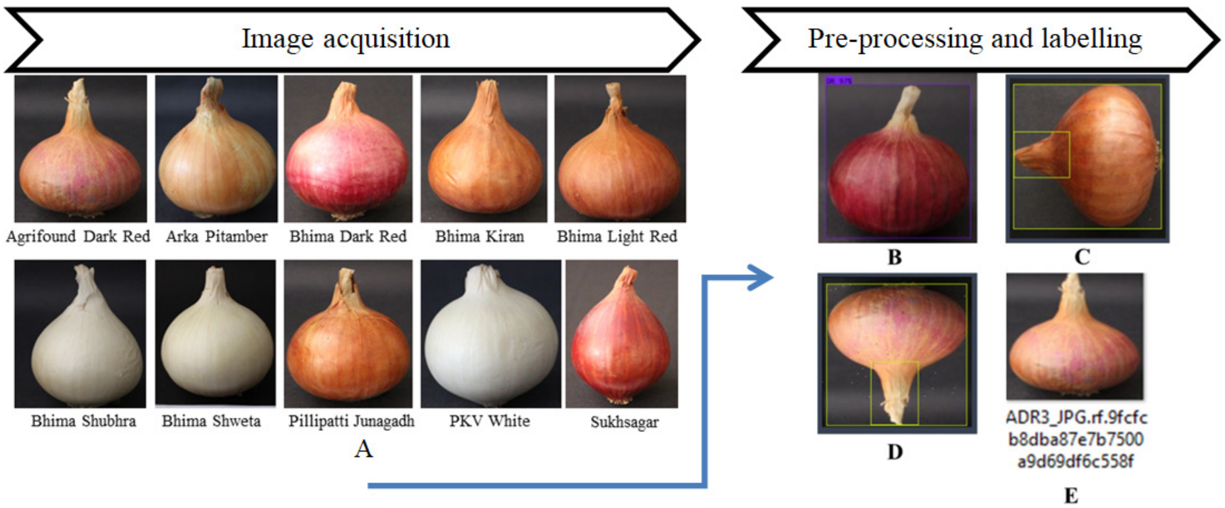


**Fig. 2:** Construction of image dataset, pre-processing and labelling (A. RGB Image dataset acquisition, B. Bounding boxing, C. Horizontal-vertical flip, D. 90° rotation, E. Labelling)

robust to different real-world conditions and reduce the risk of over-fitting. By enhancing data diversity without needing additional data, augmentation allows models to become more adaptable, accurate and resilient in practical applications (Pawara et al., 2017; Dong et al., 2024). Labelled images were then classified into respective variety folders collected in the build model folder. This directory data was split into 70% training, 20% validation and 10% testing for further training of the model.

### *Transfer learning*

In machine learning, transfer learning involves using knowledge gained from multiple applications of deep neural networks (DNNs) to improve performance on a new, related task (Behera et al., 2021). Instead of training a model from scratch, transfer learning leverages a pre-trained model, often trained on a large, general dataset and fine-tunes it for a specific task with a smaller dataset. This approach is especially valuable when labelled data is limited or when training from scratch would require extensive time and computational resources. Transfer learning offers valuable benefits for automated plant identification, especially for improving low-performance plant classification models (Kaya et al., 2019). Thus, here we considered four popular transfer learning architectures, Xception, DenseNet121, MobileNetV2 and InceptionNetV3 pre-trained on the ImageNet dataset. In this preliminary study, we deliberately used standard CNN models to assess the feasibility of classifying a limited set of 10 onion varieties based on bulb images. Given the small dataset size and exploratory nature of the work, SOTA models were excluded to avoid overfitting and unnecessary computational complexity. All CNN models were developed using the TensorFlow 2.17.1 platform with the Keras backend, programmed in Python 3 and implemented in Google Colab. The Xception model builds on ideas from Inception networks but uses depthwise separable convolutions to reduce parameters and computational costs. It has 36 convolutional layers organized into 14 modules to learn features more efficiently (Carreira et al., 1998). The DenseNet121 has 121 layers, which reduce redundant feature extraction by densely connecting layers (Swaminathan et al., 2021). MobileNet V2, with its 53 layers, utilizes depthwise separable convolutions to significantly reduce the number of operations and parameters (Howard, 2017). Finally, InceptionNetV3 with 48 layers, which combines convolutions of different kernel sizes in parallel (within its Inception modules) to capture multi-scale features were used (Xia et al., 2017). Replacing the top layers, we retained only convolutional layers for feature extraction, which is a base model. Global average pooling (GAP) was applied to the output of the base model before adding custom top layers. GAP reduces each feature map to a single value by taking the average of all its values and with a smaller dataset, it reduces the risk of over-fitting (Dogan, 2023). The first fully connected layer of 512 units with a ReLU activation function is used in the top layers. The last fully connected prediction layer with 10 neurons, according to the number of classes of the task and Softmax activation function was used. The Softmax function outputs a probability distribution across the 10 classes, enabling multi-class classification.

### *Hyperparameters*

The layers of the pre-trained models were frozen to focus on training the custom layers. For data loading, images are resized to 224x224 pixels and a batch size of 16 is used. The data is shuffled with a buffer size of 1000, cached in memory and prefetching is enabled with auto-tune for optimal input pipeline performance. The model is compiled with the Adam optimizer and a learning rate of 0.001, using categorical cross-entropy as the loss function and accuracy as the evaluation metric. The model was trained for 30 epochs to ensure sufficient learning.

### *Performance metrics*

For evaluation of our model's performance and its potential to classify onion variety images accurately, we have used accuracy, precision, recall, F1-score, Matthew's correlation coefficient (MCC), mean squared error (MSE) and confusion matrix. Accuracy indicates the model's ability to make correct predictions. Precision measures the accuracy of positive predictions, which is a ratio between the number of correct predicted positive images and the total number of positive images. Recall measures the ability of the model to identify all real positive instances (important for minimizing false negatives). F1-score provides a balance measure of performance between precision and recall when there are imbalanced classes. MCC takes into account true and false positives and negatives, providing a balanced measure even when the classes are imbalanced. It's particularly useful for binary and multi-class classification problems. MSE measures the average squared error between predicted and true values. The equations of all metrics used are provided below:

$$\text{Accuracy} = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

$$\text{Precision} = TP/(TP + FP) \quad (2)$$

$$\text{Recall} = TP/(TP + FN) \quad (3)$$

$$\text{F1-score} = 2 * (\text{Precision} * \text{Recall})/(\text{Precision} + \text{Recall}) \quad (4)$$

$$\text{MCC} = \frac{TP*TN-FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (5)$$

$$\text{MSE} = \frac{1}{n}\sum_{i=0}^{n}(Yi - \hat{Y}i)^2 \quad (6)$$

Where, TP: True positives, TN: True negatives, FP: False positives, FN: False negatives

A confusion matrix is a table that evaluates the performance of a classification model by displaying the counts of actual versus predicted classifications. It breaks down predictions into four categories: True positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). From these, one can derive important metrics such as accuracy, precision, recall, specificity and F1 score. The matrix provides detailed insights into model errors, particularly for imbalanced datasets, by showing how well the model distinguishes between classes and where it misclassifies. This allows us to identify specific areas for improvement, such as reducing false positives or false negatives.

## Results and Discussion

The main objective of this study was to determine whether it is possible to identify onion varieties based on bulb colour, size, shape, diameter, height and veinal pattern on outer scales. The automatic identification of onion bulb varieties is a critical component of precision cultivation (Fan et al., 2021), significantly advancing agricultural practices and ensuring varietal purity. Traditional methods relying on visual identification in markets are often unreliable and subjective, leading to uncertainty. To address these challenges, this study trained four transfer learning models to identify 10 selected onion varieties. Model performance was rigorously evaluated using metrics such as accuracy, precision, recall, F1 score, MCC and MSE, providing a comprehensive assessment of their effectiveness. To investigate this, we used bulb-based identification based on image classification using a deep learning approach.

### *Training stage*

Table 2 compares four CNN architectures, Xception, DenseNet121, InceptionNetV3 and MobileNetV2 based on model size, training and validation performance. DenseNet121 emerges as the top performer, achieving the highest training accuracy of 97.41% and tying with MobileNetV2 for the best validation accuracy of 95.56%, with a smaller model size of 35 MB. MobileNetV2 offers a strong balance of performance and efficiency, maintaining competitive accuracy with a moderate size of 46 MB. Both models showed consistency in accuracy and loss. InceptionNetV3 is the smallest at 31 MB, though it lags slightly in accuracy compared to the top two. Xception, while accurate during training, ranks lowest due to its larger size (92 MB) and lower validation accuracy of 88.14%. A detailed variation in training accuracy and loss per iteration or epoch is given in Fig. 3. From the graph, it was observed that training accuracy and loss of InceptionV3 and Xception showed inconsistent increases in accuracy, whereas a smooth graph was obtained for DenseNet121 and MobileNetV2.

The performance of different deep learning architectures during the testing phase is presented in Table 3. In contrast, the Xception architecture showed comparatively lower performance, yielding a test accuracy of 88.14% and a higher test loss of 0.49, at the lowest. MobileNetV2 attained a test accuracy of 93.22% with a test loss of 0.19 and stood at third. This was closely followed by InceptionNetV3, which achieved a test accuracy of 94.55% and a test loss of 0.26, securing the second. Among the evaluated models, DenseNet121 exhibited superior performance, recording the highest test accuracy (94.92%) along with the lowest test loss (0.14) and stands at first. The accuracy rates obtained in this study are in agreement with those obtained by Taner *et al*. (2024), who applied seven deep learning models, VGG16, VGG19, InceptionV3, MobileNet, DenseNet201, Xception and ResNet152V2 for the classification of apple varieties and obtained accuracy ranging from 91-97%, with higher in DenseNet201 (64 filters of size 7×7). Similarly, Kozłowski et al. (2019) achieved an accuracy of over 93% using AlexNet and ResNet18, employing their custom-designed CNN for the classification of barley varieties.

**Table 2:** Results of training and validation at building stage

| Architecture | Model size (MB) | Training results | | Validation results | | Ranking |
|---|---|---|---|---|---|---|
| | | Accuracy (%) | Loss (%) | Accuracy (%) | Loss (%) | |
| Xception | 92 | 94.83 | 0.15 | 88.14 | 0.34 | 4 |
| DenseNet121 | 35 | 97.41 | 0.09 | 95.56 | 0.17 | 1 |
| InceptionNetV3 | 31 | 93.65 | 0.21 | 94.94 | 0.24 | 3 |
| MobileNetV2 | 46 | 96.31 | 0.09 | 95.56 | 0.15 | 2 |

Testing stage

**Table 3:** Results of testing stage

| Architecture | Test accuracy (%) | Test loss (%) | Ranking |
|---|---|---|---|
| Xception | 88.14 | 0.49 | 4 |
| DenseNet121 | 94.92 | 0.14 | 1 |
| InceptionNetV3 | 94.55 | 0.26 | 2 |
| MobileNetV2 | 93.22 | 0.19 | 3 |

Precision, recall, F1 score, MCC and MSE were used to evaluate the performance of four models: DenseNet121, InceptionNetV3, MobileNetV2 and Xception. The performance metrics of the four models are presented in Table 4. DenseNet121 outperformed the others in most metrics, achieving the highest precision (95.76%), recall (94.92%), F1 score (94.82%) and MCC (94.47%), indicating its superior balance between accurate and reliable predictions. InceptionNetV3 closely followed, with a precision of 95.14%, recall of 94.55%, F1 score of 94.55% and MCC of 94.00%, showing strong performance but slightly below DenseNet121. MobileNetV2 ranked third, achieving a precision of 93.69%, recall of 93.22%, F1 score of 93.21% and MCC of 92.53%, reflecting good performance but with a noticeable gap compared to the top models. Xception, with the lowest precision (91.04%), recall (88.14%), F1 score (87.63%) and MCC (87.21%), showed a higher rate of misclassifications and weaker consistency. In terms of error minimization, MobileNetV2 had the lowest mean squared error (MSE) of 0.11, making it highly effective for tasks sensitive to prediction errors. DenseNet121 followed with an MSE of 0.94, while InceptionNetV3 (1.48) and Xception (2.15) exhibited progressively higher error rates. DenseNet121 emerged as the most balanced and reliable model, combining high accuracy, strong predictive reliability and minimal false predictions, while MobileNetV2 demonstrated exceptional error minimization capabilities.

These metrics provide a comprehensive view of model reliability, balancing true positive predictions with the minimization of false positives and negatives, as well as prediction errors. DenseNet121 consistently demonstrated superior performance, achieving the highest precision (95.76%), recall (94.92%), F1 score (94.82%) and MCC (94.47%). These results underscore DenseNet121's ability to balance sensitivity and specificity effectively, aligning with findings in previous studies that emphasize its robustness in feature extraction and predictive accuracy (Huang *et al*., 2017). Its slightly higher MSE (0.94) compared to MobileNetV2 may reflect its emphasis on overall classification performance rather than minimizing individual errors. InceptionNetV3 performed closely to DenseNet121, achieving a precision of 95.14% and F1 score of 94.55%. While its recall (94.55%) and MCC (94.00%) were marginally lower than DenseNet121, it still exhibited strong consistency. This aligns with prior research highlighting InceptionNetV3's efficacy in capturing hierarchical features through its inception modules, albeit with slightly reduced sensitivity compared to DenseNet architectures (Szegedy et al., 2016). MobileNetV2 emerged as an efficient alternative, achieving the lowest MSE (0.11), indicating minimal prediction errors. Its overall performance in terms of precision (93.69%), recall (93.22%), F1 score (93.21%) and MCC (92.53%) was commendable, though it lagged behind DenseNet121 and InceptionNetV3. The low MSE of MobileNetV2 is consistent with its lightweight architecture and focus on computational efficiency, as reported by (Sandler et al., 2018). Xception showed relatively lower performance across all metrics, with precision (91.04%), recall (88.14%), F1 score (87.63%), MCC (87.21%) and the highest MSE (2.15). These findings reflect its susceptibility

**Table 4:** Performance metrics of convolutional neural network

| Model | Precision (%) | Recall (%) | F1 score (%) | MCC (%) | MSE |
|---|---|---|---|---|---|
| Xception | 91.04 | 88.14 | 87.63 | 87.21 | 2.15 |
| DenseNet121 | 95.76 | 94.92 | 94.82 | 94.47 | 0.94 |
| InceptionNetV3 | 95.14 | 94.55 | 94.55 | 94.00 | 1.48 |
| MobileNetV2 | 93.69 | 93.22 | 93.21 | 92.53 | 0.11 |

**Table 5:** Comparison of model performance in classification of onion varieties

| *Model* | *Correct Classifications* | *Key Misclassifications* | *Strengths* | *Areas for Improvement* |
|---|---|---|---|---|
| Xception | High for most classes | BK as AP, PKV as BSS | Robust performance across classes | BK, PJ, PKV overlap, misclassifications in similar classes |
| DenseNet121 | Strong performance across classes | BK as AP, PKV as BSS, SK as PKV | Accurate feature extraction | Overlap in features between BK, PKV and others |
| InceptionV3 | High performance, near-perfect accuracy | AP as BK, PKV as BSH, SK as ADR | High overall accuracy, few misclassifications | Confusion in AP, PKV and SK classes |
| MobileNetV2 | Strong accuracy | AP as BK, BSH as BSS, BSS as BSH | Fast and efficient model | BSH and BSS overlap, AP as BK |

(ADR: Agrifound Dark Red, AP: Arka Pitamber, BDR: Bhima Dark Red, BK: Bhima Kiran, BLR: Bhima Light Red, BSH: Bhima Shubhra, BSS: Bhima Shweta, PJ: Pillipatti Junagadh, PKV: PKV White, SK: Sukhsagar)

to higher false predictions and lower reliability, possibly due to its more complex architecture, which may require larger datasets or extensive fine-tuning to achieve comparable results (Chollet, 2018).

The confusion matrices for each of the four models, Xception, DenseNet121, InceptionV3 and MobileNetV2, reveal valuable insights into the classification performance, highlighting both strengths and weaknesses (Table 5). Confusion matrices for each model are presented in Fig 4. The matrix represents the relationship between the model's predictions and the true labels of onion bulb images. The diagonal elements represent the number of correct predictions made by the model for each class. These are the instances where the predicted class matches the actual class, indicating the model's successful classification for that particular category. On the other hand, the off-diagonal elements represent the misclassifications, where the model has predicted the wrong class. These are the values outside the diagonal that indicate how often the model has confused one class with another.

Xception shows a tendency for misclassifications, particularly for the Agrifound Dark Red, Bhima Light Red, and PKV White varieties. For instance, the Agrifound Dark Red is occasionally misclassified as Sukhsagar or Bhima Light Red, and PKV White is often confused with Bhima Shweta. This is reflected in the model's lower precision (91.04%) and recall (88.14%), suggesting that Xception struggles with distinguishing between certain classes, leading to higher false positives and false negatives. In contrast, DenseNet121 performs significantly better, with a precision of 95.76% and a recall of 94.92%, indicating fewer misclassifications across the board. The confusion matrix for DenseNet121 shows minimal errors, particularly in Arka Pitamber and Bhima Kiran, where misclassifications occur only rarely. This indicates that DenseNet121 exhibits robust class differentiation, making it the most reliable model in terms of accuracy and consistency. InceptionV3 follows closely, with precision (95.14%) and recall (94.55%) values almost identical to those of DenseNet121. The confusion matrix for InceptionV3 reveals occasional confusion between the PKV White and Pillipatti Junagadh varieties, contributing to its slightly lower performance compared to DenseNet121. MobileNetV2, while showing the lowest MSE (0.11), has a precision of 93.69% and a recall of 93.22%, slightly lower than both DenseNet121 and InceptionV3. The model's confusion matrix indicates that classes like BSH and BSS are frequently misclassified, contributing to a drop in performance. Despite this, MobileNetV2's MSE suggests it is the most consistent in terms of the proximity of predictions to true values, making it an ideal choice when computational efficiency is a priority. The overall F1 scores for all models reflect the trade-off between precision and recall, with DenseNet121 achieving the highest score (94.82%), followed by InceptionV3 (94.55%), MobileNetV2 (93.21%) and Xception (87.63%). These findings suggest the critical role of model fine-tuning and class balancing in improving precision and recall for certain classes. The analysis of these confusion matrices, in conjunction with performance metrics like MSE and MCC, highlights the importance of selecting the right model based on the specific needs of the application. Across the classes, the white-coloured Bhima Shubhra and Bhima Shweta varieties were particularly challenging, with all the models struggling to differentiate between them except DenseNet121. Similarly, Arka Pitamber and Bhima Kiran were misclassified and confused by all the models except DenseNet121.

The results of this study demonstrate the robustness and reliability of DenseNet121 over MobileNetV2 and InceptionV3 models in onion variety identification. The reliability of DenseNet121 stems from its dense connectivity architecture, where each layer receives inputs from all preceding layers. This feature allows the model to reuse features effectively, promoting better gradient flow and mitigating the vanishing gradient problem (Peng et al., 2024; Sangeetha et al., 2024). Additionally, it enables the model to capture intricate details and patterns in the dataset, which is crucial for distinguishing visually similar onion varieties. The performance of the Xception model

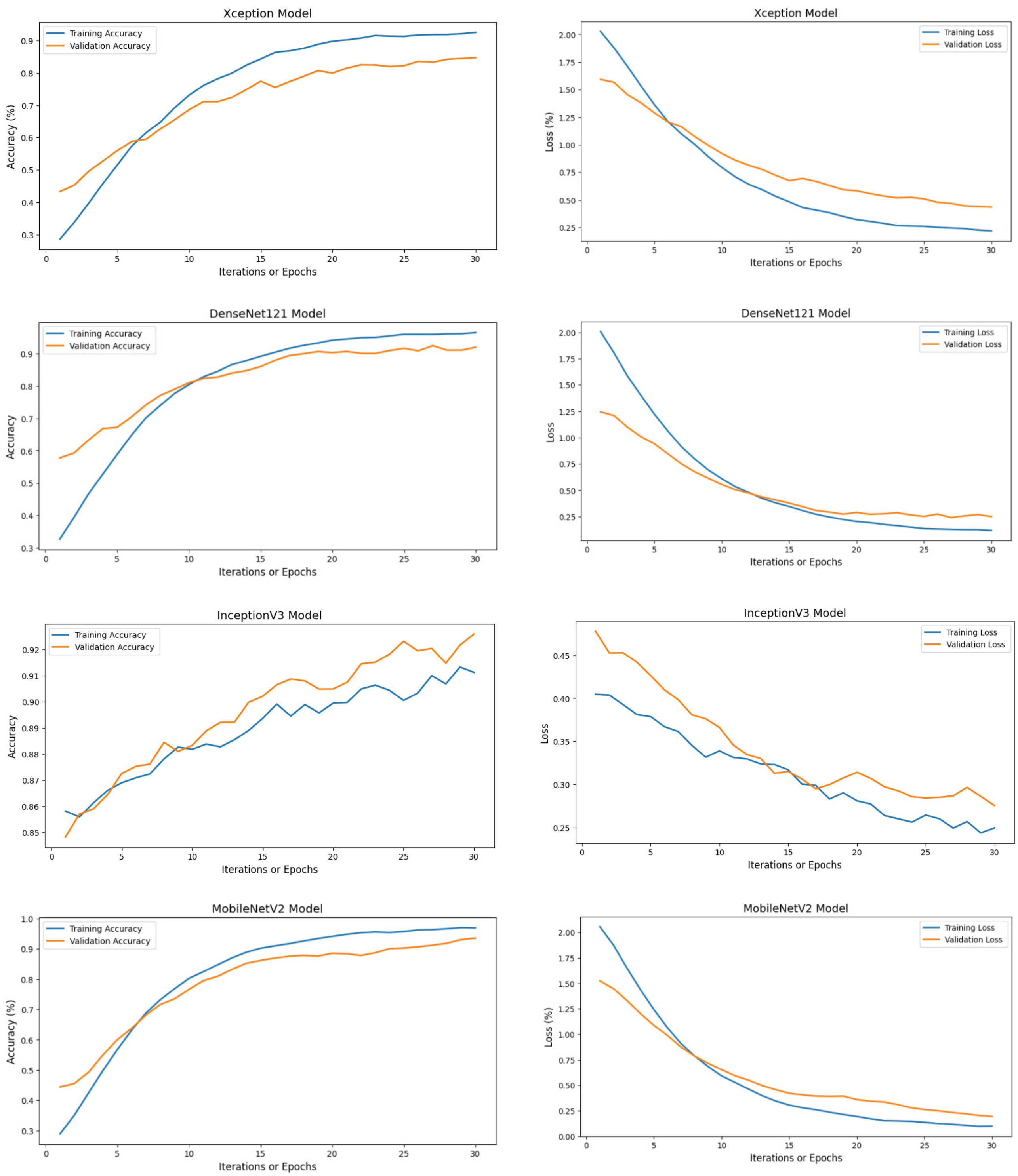


**Fig. 3:** Training and validation accuracy and loss of four different CNN models

for onion variety identification raises questions about its effectiveness and reliability compared with DenseNet121 and MobileNetV2. The tendency to produce false positives poses significant challenges in practical applications like onion sorting and grading, as it can result in costly errors. Moreover, the Xception model's low precision, recall and F1 score highlight its difficulty in effectively capturing the unique characteristics of various onion varieties.

DenseNet121 emerged as the most balanced model, excelling in accuracy, recall and reliability, making it well-suited for applications requiring robust classification performance. MobileNetV2, with its minimal prediction

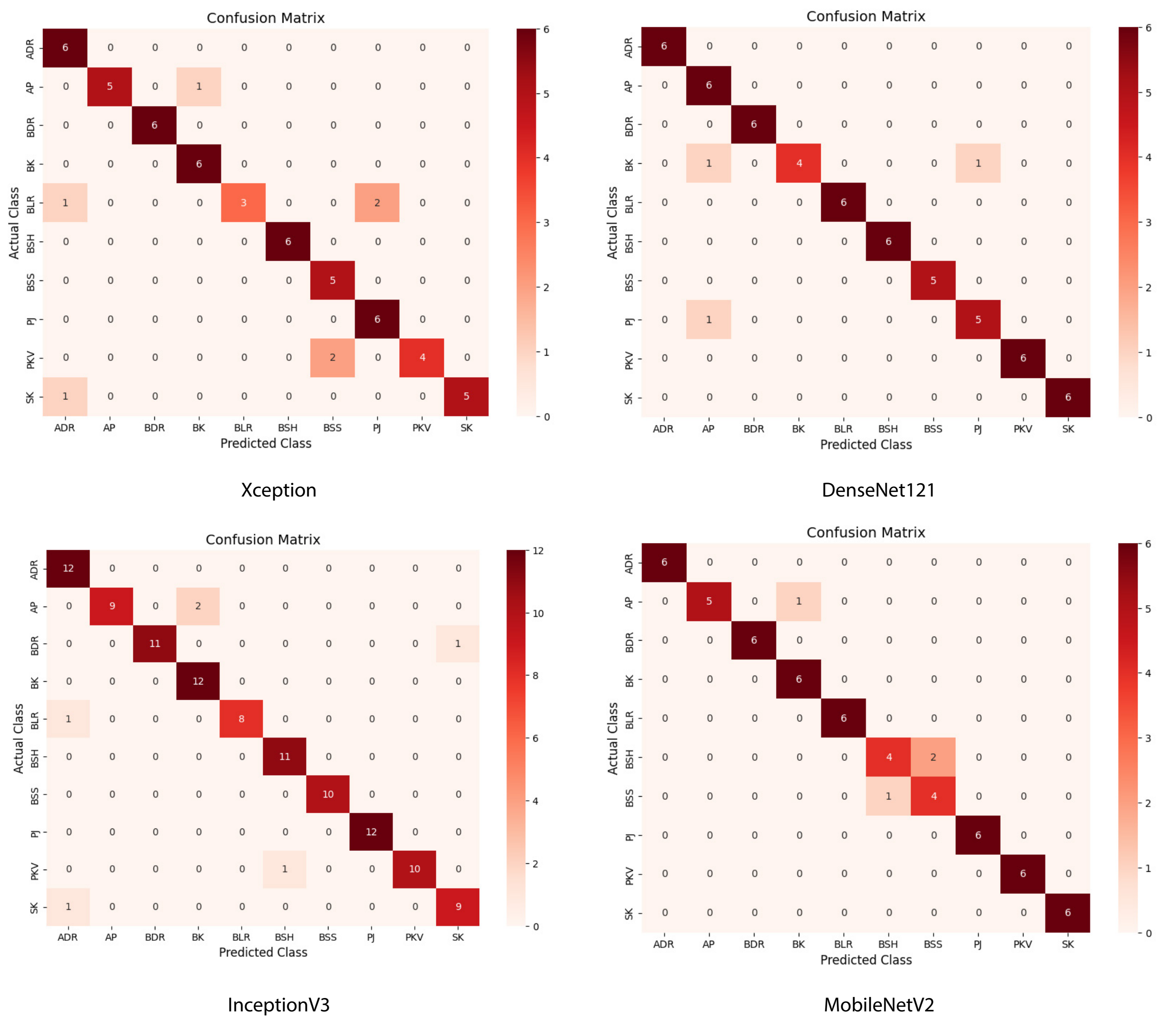


**Fig. 4:** Confusion matrices showing model-wise classification performance of 10 onion varieties. (Diagonal values represent correct classifications, while off-diagonal elements highlight frequent misclassifications. ADR: Agrifound Dark Red, AP: Arka Pitamber, BDR: Bhima Dark Red, BK: Bhima Kiran, BLR: Bhima Light Red, BSH: Bhima Shubhra, BSS: Bhima Shweta, PJ: Pillipatti Junagadh, PKV: PKV White, SK: Sukhsagar)

errors, proved highly effective for scenarios prioritizing error minimization and computational efficiency. InceptionV3 offered a strong balance between accuracy and reliability, while Xception showed the need for further optimization to enhance predictive consistency. Future work could explore hyperparameter tuning and dataset augmentation to further improve model performance. However, the dataset structure plays a crucial role in evaluating model efficiency. This study focused on images from *rabi*-harvested produce. Expanding the dataset to include produce from *kharif*, *late-kharif* and *rabi* seasons would provide a more comprehensive understanding of seasonal and spatial variability. Additionally, the limited dataset size and storage duration used in this study may have restricted the models' ability to capture diverse features. This classification framework has potential real-world applications in automated grading systems, mobile-based varietal verification for farmers, and digital traceability tools for seed certification agencies and traders.

This study demonstrates promising results using a Limitations dataset of 10 onion varieties; it does not yet account for environmental and seasonal variability. All images were collected from *rabi*-harvested produce at a single location, which may limit generalizability. Additionally, certain visually similar varieties, such as Bhima Shweta and Bhima Shubhra, were frequently misclassified by some models, indicating the need for higher intra-class resolution. Further, the image dataset lacks samples across different storage durations or physiological ages, which could affect model robustness. These limitations point to the need for multi-season data and larger varietal representation in future studies.

## Conclusion

Onion is a crop of immense importance and a dominant player in the international market among agricultural commodities. Accurate identification of onion varieties is crucial for pricing, quality assurance and consumer preference. Artificial intelligence (AI) and Machine Learning (ML) offers a superior alternative to the faulty and dubious methods of visual examination and individual perception in image classification tasks, achieving high accuracy and precision. This study establishes the feasibility of using deep learning models for the classification of Indian onion varieties based on bulb images. Among the models tested, DenseNet121 demonstrated the highest reliability and performance, owing to its dense connectivity and efficient feature extraction. The exclusion of state-of-the-art (SOTA) models was intentional, as their higher complexity and data requirements could lead to overfitting and would not be justified at this exploratory stage. The chosen models are efficient, well-established and appropriate for small datasets, allowing for a reliable baseline assessment. These findings support the potential of computer vision tools in enhancing the accuracy and speed of varietal identification, with direct applications in grading, sorting and quality assurance systems. Given the diversity of onion cultivars and environmental conditions across India, future research should include expanded datasets covering multiple growing seasons, storage durations and a wider range of varieties. Incorporating more advanced architectures, such as Vision Transformers or ensemble models, may further enhance classification accuracy. This work lays the foundation for building scalable, AI-driven platforms for onion variety verification in breeding, seed certification and supply chain management.

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## सारांश

प्याज़ एक अत्यंत महत्वपूर्ण व्यावसायिक सब्ज़ी है, जिसका व्यापक रूप से विश्वभर में उत्पादन और व्यापार किया जाता है। प्याज़ की किस्मों की सटीक पहचान मूल्य निर्धारण, गुणवत्ता सुनिश्चित करने, अनुरेखण और उपभोक्ता पसंद के लिए अत्यंत आवश्यक है, लेकिन विभिन्न किस्मों में उच्च आकृति-आधारित समानता के कारण यह कार्य चुनौतीपूर्ण बना रहता है। इस अध्ययन में पहली बार भारतीय प्याज़ की किस्मों को कंद की छवियों के आधार पर deep learning तकनीक से वर्गीकृत करने का प्रयास किया गया है। हमने 10 लोकप्रिय प्याज़ किस्मों के एक विशेष रूप से तैयार किए गए चित्र डेटासेट पर चार प्री-ट्रेंड कॉन्वोल्यूशनल न्यूरल नेटवर्क (DenseNet121, InceptionV3, MobileNetV2 और Xception) के प्रदर्शन का मूल्यांकन किया। परिणामों से पता चला कि DenseNet121 ने सभी मॉडलों को पीछे छोड़ते हुए सर्वोच्च प्रिसीजन (95.76%), रिकॉल (94.92%), F1 स्कोर (94.82%) और न्यूनतम माध्य वर्ग त्रुटि 0.94 प्राप्त की, जो इसकी असाधारण विश्वसनीयता और सटीकता को दर्शाता है। इसकी सघन कनेक्टिविटी संरचना ने सूक्ष्म विशेषताओं को प्रभावी रूप से कैप्चर किया, जिससे यह व्यावहारिक अनुप्रयोगों के लिए सबसे उपयुक्त साबित हुआ। InceptionV3 और MobileNetV2 ने भी प्रतिस्पर्धी परिणाम दिए, जिसमें MobileNetV2 ने कम्प्यूटेशनल दक्षता दिखाई, लेकिन कुछ गलत वर्गीकरण में कठिनाई का सामना करना पड़ा। Xception, दक्ष होने के बावजूद, सबसे कम प्रदर्शन सूचकांक के साथ रहा, जिसमें प्रिसीजन 91.04% और रिकॉल 88.14% थी, तथा इसमें उल्लेखनीय गलत वर्गीकरण पाए गए। ये निष्कर्ष DenseNet121 की स्वचालित प्याज़ किस्म पहचान में क्षमता और कृषि डेटासेट्स में जटिल विविधताओं को संबोधित करने में इसकी श्रेष्ठता को उजागर करते हैं। यह अध्ययन दर्शाता है कि Deep learning तकनीक प्याज़ की किस्मों की पहचान को स्वचालित करने, छंटाई, ग्रेडिंग तथा बीज श्रृंखला सत्यापन प्रणाली को समर्थन देने में महत्वपूर्ण भूमिका निभा सकती है। भविष्य में अनुसंधान को और अधिक किस्मों तथा मौसमी डेटासेट तक विस्तारित किया जाना चाहिए, ताकि वास्तविक परिस्थितियों में इसका सफलतापूर्वक उपयोग किया जा सके।