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Attention-enhanced VGG-16 architecture for precision weed detection in wheat fields

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ABSTRACT

This study delineates five advanced convolutional neural network designs that employ deep learning for the classification of wheat weeds. The dataset consists of greyscale photos taken in agricultural fields, enhanced with RGB lighting and cropped to 256×256×3 pixels. Normalization, batch-wise augmentation, contrast stretching, or histogram equalization were all part of the preprocessing that improved picture quality and model learning efficiency. These enhancements developed feature extraction by increasing picture contrast and homogeneity. A VGG16-based model with further Conv2D layers and spatial attention is one of the five models recommended. An additional design, inspired by ResNet50 that applies residual blocks and worldwide average pooling. A hybrid RNN integrated ICNA-CNN or LSTM for spatial-temporal content learning is another. Lastly, InceptionResNetV2 is enhanced with CNN layers and a query-key attention mechanism. We used the Adam optimizer and categorical cross-entropy to estimate the loss throughout the training for the round. At the end, all the models had ReLU activation, batch normalization, MaxPooling2D, and a dropout charge of 0.5 to keep them from overfitting. Upon evaluating their performance based on accuracy, recall, reliability, and training loss, VGG16 emerged as the standout model, achieving an impressive 99.07% precision and a remarkably low training loss of just 0.0079. The study determined that VGG16 is the optimal choice for precise wheat–weed categorization because to its superior generalizability and accuracy.

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1. INTRODUCTION

Particularly in precision farming, the uses of artificial intelligence (AI) and machine learning in the farming sector have resulted in revolutionary shifts. Weed control, which greatly reduces agricultural yield and quality, is one of the biggest problems in contemporary farming. Mechanical removal and human observation, the two mainstays of traditional weed identification procedures, are both tedious and prone to human mistake [1]–[4]. Traditional methods don't work for making decisions in real time or for large areas of farming [5]–[9]. Many people are enthusiastic about smart farming and computer vision and computer vision techniques for automated crop and weed classification due to the increasing demand for sustainable agriculture and the global trend towards automation [10]–[15].

Weed infestations can severely diminish crop quality and quantity if not promptly discovered and controlled; this is especially true of wheat, a staple crop around the world. In order to minimize the use of herbicides, lessen the environmental effect, and increase crop health, it is crucial to detect weeds among wheat crops early and accurately. Automated visual classification systems that use deep learning are a faster and cheaper way to do inspections than having people do them.

These systems study field images to recognize regions where wheat plants remain healthy and fields where weed growth is on the rise. Convolutional neural networks (CNNs) have fundamentally revolutionized this domain by enabling models to identify spatial patterns and extract intricate visual features from agricultural photographs [16]–[22]. CNNs and other deep learning architectures are exceptionally effective at image classification because they autonomously learn relevant properties without requiring manual human intervention. The presence of background noise, variations in lighting, or impediments might nevertheless cause agricultural pictures to occasionally display irregularities. As a result, high-quality images and reliable model training depend on effective preprocessing techniques. Normalizations, contrast stretching, and histogram equalization are common ways to standardise image data and improve crucial visual signals. This allows for better learning and generalisation [23]–[27].

These models appear capable of distinguishing between various weed species by recognizing subtle changes in leaf shape, coloration, and texture across various environmental conditions. Moreover, agricultural imagery can often be inconsistent due to background clutter, changing sunlight conditions, or physical obstructions. Achieving high-quality images and training robust models demands effective preprocessing methods. Common approach such as normalization, contrast improvement, and histogram equalization improves image uniformity and amplify essential visual attributes. This facilitates better feature extraction and knowledge transfer, which is critical for differentiating wheat from weed species. Choices regarding dataset selection, preprocessing workflows, model design, and training protocols significantly influence the final classification performance. Publicly available resources like the wheat-weed dataset enable researchers to train and evaluate machine learning models.

These datasets typically include RGB field images captured under diverse weather conditions, reflecting the complexity of real-world agricultural environments. Nevertheless, such datasets often suffer from class imbalances—for instance, containing far more weed images than healthy crop samples. Addressing this disparity is essential to prevent biased model outputs and ensure reliable classification across all categories. Hyperparameters like learning rates, dropout ratios, activation functions, and optimizer types need careful tuning for each model. The Adam optimizer is broadly preferred for classification tasks due to its efficient learning and rapid convergence. Activation functions such as rectified linear unit (ReLU) enhance training by introducing non-linearity and mitigating the vanishing gradient problem.

Output-stage softmax layers convert raw scores into probability distributions, enabling multi-class categorization. Loss functions such as categorical cross-entropy guide optimization by penalizing predictions according to their deviation from true labels. A rigorous data-splitting strategy, typically involving stratified train–test divisions, is essential for thoroughly validating model enhancement and ensuring generalization.

2. LITERATURE REVIEW

This section discusses the most pertinent earlier study related to this subject, as summarized in Table 1. Singh suggests comprise supplementary climatic and topographical information alongside high-resolution satellite images to forecast wheat yield differences at the farm level using a machine learning technique. Training and validation of the model relied on more than 10,000 data points collected from 45 farms in the Fergana Valley in central analyses monitoring agricultural resources (MARS) agricultural yield forecasting system data to assess neural network models for agricultural yield forecasting.

We looked at how gradient-boosted decision trees (GBDTs) and long short-term memory (LSTM) models did compared to 1D convolutional neural networks (1D CNNs). LSTM was better at predicting Germany's soft wheat yields than GBDT, but the findings were different for each case. The research highlights the need of involving stakeholders, make models easy to understand, and show how well deep learning works for automated feature extraction and prediction. It also talks about how machine learning may be used to guess how much five crops in Rajasthan, India will yield. Random forest outperformed support vector machine (SVM), gradient descent, LSTM, and Lasso regression.

Recently, researchers have created a lot of deep learning (DL)-based solutions that use different remote sensing (RS) datasets and DL architectures. These technologies produce precise outcomes for crop mapping and yield forecasting. These solutions also need to figure out how to deal with the difficulties of not having enough training data, building models that are helpful, efficient, and can be utilized on a wide range of sites and crops. These are all important for proving that they work and can be used in different farming situations.

Table 1. Literature on state-of art research

Author(s)	Methodology	Dataset	Accuracy (%)
Kaunalakis *et al.* (2019)	AlexNet, VGG-F, VGG-VD16, Inception-VI, ResNet50, ResNet101	Monochrome Camera	ResNet-50 with 96.10
Lam *et. al*. (2021)	VGG16	DJI Phantom 3 and 4	92.1
Liu *et al.* (2021)	AlexNet, VGG16, GoogleNet	Variable rate sprayer	VGG-16 achieved 96.00
Milioto *et al.* (2018)	CNN + Fully Convolutional Network (FCN)	Bonn Dataset (RGB + NIR)	91.88
Olsen *et al*. (2019)	Ineption-V3 and ResNet-50	Danish Weed Dataset	95.1
Dyrmann *et al.* (2016)	HOG + SVM classifier	Danish Agricultural Dataset	86.2
Yu *et al.* (2019)	Deep Residual Network (ResNet-50)	Custom wheat field dataset (China)	93.2
Lottes *et al.* (2017)	Encoder–Decoder CNN (SegNet-based)	Sugar Beet Dataset	90.3
D. S. Ferreira *et al.* (2017)	CNN with Handcrafted Preprocessing	Real field images in Brazil	88.4
Proposed Model	VGG16	Wheat-Weed Dataset	**99.07**

3. METHOD

The dataset consists of around 10,046 images from wheat fields in Raisen Road, Madhya Pradesh, India (23°15'40.5"N 77°38'60.0"E), captured during the Dec 2024–Jan 2025 crop season. The wheat-weed dataset is a great place to start when creating and testing machine learning models that can tell the difference between healthy wheat fields and weedy ones (Figure 1). This collection has 10,046 RGB pictures, with the "Normal" and "Weed" segments each having 5,023 photos. The "Normal" class has 2,024 photographs of wheat crops that don't have any weeds in them, and the "Weed" class has 8,022 pictures showing different kinds of weeds growing among wheat plants. The realistic relevance of the analysis is strengthened by the considerable variation between the two classes, which mirrors a frequent challenge found in real-world farming environments. This data plays a critical role in the training, evaluation, and validation of the different segmentation and classification techniques introduced in this work—like CNNs, RNNs, and VGG-16. These algorithms will contribute to improving the precision of weed localization and wheat field monitoring, thereby supporting advancements in precision agriculture.

Figure 1. Weed picture of data

3.1. Pre-processing

In the preprocessing phase of the wheat-weed classification workflow, contrast stretching and histogram equalization serve as two fundamental contrast improvement techniques. These methods significantly boost image quality and simplify feature discrimination within deep learning models. For the present, histogram equalization functions as a nonlinear enhancement approach that increases overall contrast by redistributing pixel intensity levels. These methods used together normalize image intensity and contrast, hence allowing models like VGG16 and EfficientNet to gain stronger and more discriminative properties.

Contrast stretching enhances image quality by emphasizing subtle details in leaf morphology that may address certain deficiencies and by expanding the range of intensity values. Histogram equalization improves the appearance of leaf images through the adjustment of pixel intensity levels. This method creates a more uniform distribution of intensities across the image, thereby improving the visibility of features linked to nutrient disorders, such as chlorosis or necrosis. Figure 2 displays enhanced images of both healthy plants and weeds, showing greater clarity and feature distinction following the application of contrast stretching methods (as illustrated in Figure 3).

Figure 2. Normal and weed photographs after applying contrast stretching

Figure 3. Normal and weed images after applying histogram equalization

4. PROPOSED MODEL

Inherently applying the design and assessment of five DL models, this paper offers a thorough method to wheat-weed categorization. The data came from grayscale photos taken in agricultural fields. They were preprocessed by changing them to RGB format and scaling them to 256×256×3 pixels to meet the needs of CNN-based architectures. Batch-wise augmentation and normalization were two more preprocessing methods that helped make the model more generalizable. Model 1 uses EfficientNetV2B0 to extract features. This model has convolutional layers and a custom attention strategy to make it better. Model 2 improves learning spatial features by adding more Conv2D layers and attention to a pretrained VGG16 base. Model 3 is based on ResNet50 and has residual blocks and global average pooling to extract strong hierarchical features. Model 4 shows a hybrid ICNA-CNN and LSTM architecture in which the LSTM layers act like sequential dependencies while the CNN layers collect spatial information. Using InceptionResNetV2, Model 5 highlights crucial visual areas. CNN and attention layers driven by Query-Key transformation make this model more refined. Trained for 100, each iteration employs the Adam optimizer to account for categorical cross-entropy loss; all models-employ ReLU activation, batch normalization, MaxPooling2D, & dropout (0.5). We checked the model's accuracy, precision, and recall to make sure it was good at recognizing plant species. Table 2 represents the steps of the proposed model algorithm and Figure 4 shows the proposed model flowchart.

Table 2. Proposed model algorithm-1

Step	Description
Step 1	Wheat-Weed Dataset
Step 2	Wheat-Weed Dataset Wheat-Weed Dataset Wheat-Weed Dataset.
Step 3	Model Selection, EfficientNetV2 + CNN + Attention, VGG16 + Conv2D + Attention, Custom ResNet50, ICNA-CNN + LSTM, InceptionResNetV2 + CNN + Attention
Step 4	Adjust the hyperparameters of the model, such as the ReLU activation, batch normalization, max pooling, and dropout layers
Step 5	Validate model performance on a validation split of the dataset
Step 6	Testing and Grouping Use wheat-weed photos that the trained models haven't seen before to test them. Use classification to tell the difference between wheat and weed classes
Step 7	Use metrics, ROC, and the Convergence curve to rate each model

4.1. Model 1: efficientNetV2 for wheat-weed classification

The input photos, which were initially in black and white, are changed to RGB and resized to 256×256×3 to fit the model's input requirements. After feature extraction, several convolutional layers and a specific attention mechanism are used to enhance the relevant features. This helps the model focus on the most important elements of the input data, which makes it better at things like classifying pictures or finding objects. The model architecture includes ReLU activations and MaxPooling2D layers to make it non-linear or lower its dimensionality. Dropout is used at a rate of 0.5 in completely connected layers to stop overfitting. Recall, precision, and accuracy are all ways to measure performance. Figure 5 shows the layered architecture of the model.

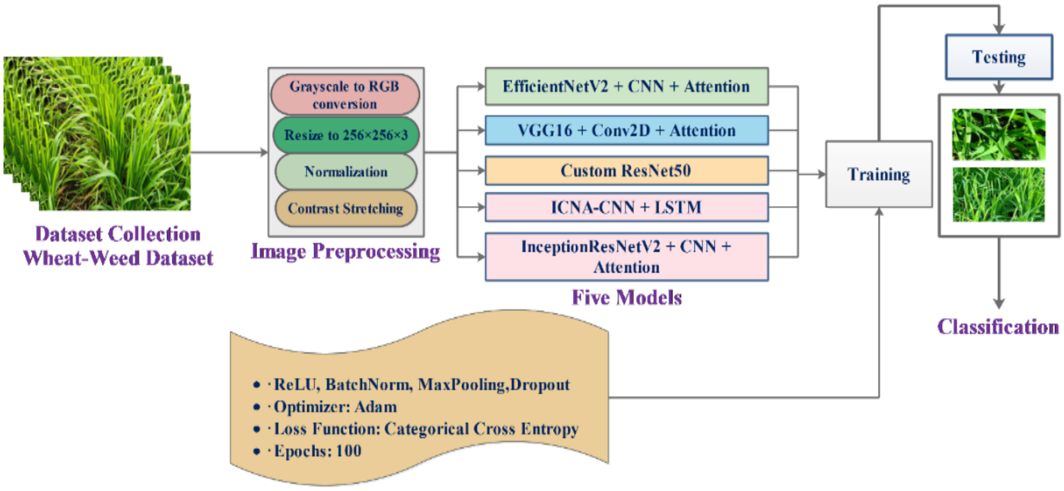

Figure 4. Proposed flowchart

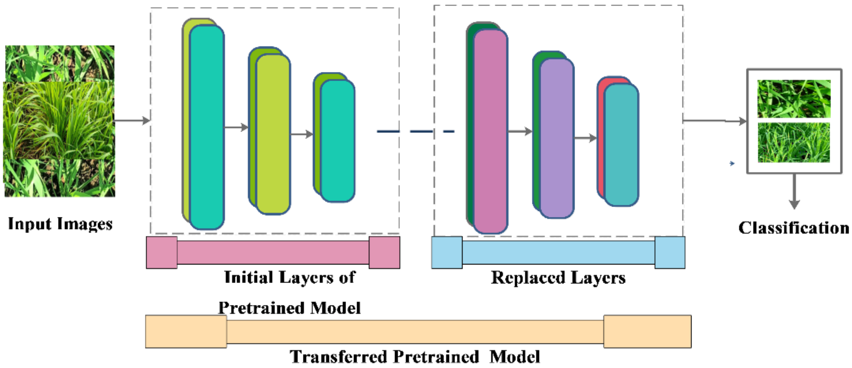

Figure 5. Layered architecture for models

4.2. Model 2: VGG16 for wheat-weed classification

To extract strong hierarchical attributes from agricultural photos, the VGG16-based approach uses a pretrained VGG16 network. In order to make the greyscale photographs work with VGG16, we had to resize them and change their format to RGB. Three more Conv2D layers with ReLU activation and MaxPooling are superimposed on top of the pretrained base to make the feature maps even better. Metrics for performance include recall, precision, and accuracy.

4.3. Model 3: ResNet50 for wheat-weed classification

After every convolutional layer, the model employs batch normalization, and for spatial reduction, it makes use of MaxPooling2D. It is common practice to compress the feature maps using global average pooling before to adding the last thick layers. To build the model, we used categorical cross-entropy for loss and the adam-optimizer, checked its performance using recall, precision, and accuracy.

4.4. Model 4: ICNA-CNN with LSTM-based RNN for wheat-weed classification

To extract spatial features, this deep learning model uses an ICNA-CNN, and to capture sequential relationships, it uses an LSTM, or long short-term memory, network. The three convolutional layers that operate with increasing filters (32, 64, 128) process greyscale input images with dimensions of 256×256×1. Layers employ ReLU activation/MaxPooling2D to reduce dimensions while extracting and condensing spatial data. Using CNNs for spatial learning and long short-term memories (LSTMs) for sequential analysis, this hybrid method improves classification performance.

4.5. Model 5: InceptionResNetV2 with CNN and attention for classifying wheat and weeds

To improve the performance of categorizing, our cutting-edge deep learning model brings together a pretrained Inception-ResNet for pulling out features, along with CNN layers and an attention mechanism. The top-layer-less InceptionResNetV2 applies residual and Inception modules to capture hierarchical and multi-scale properties. We add a bespoke attention layer that normalizes the model using Softmax after Query and Key transformations to compute attention weights, which further improves model focus. To keep things from overfitting, we added two dense layers- one with 512 units and another with 256- and finally experimented with recall and accuracy. Here's a consolidated hyperparameter details table comparing all five models (EfficientNetV2, VGG16, ResNet50, ICNA-CNN+RNN, and InceptionResNetV2) used for Wheat-Weed Classification (Figure 6), which shows the Hyperparameter details.

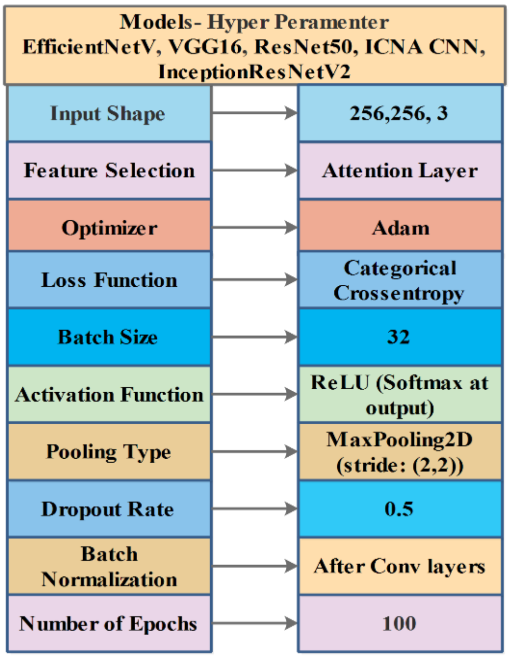

Figure 6. Hyperparameter details

5. RESULTS AND DISCUSSION

Table 3 shows the evaluation metrics for five different deep learning models that were used to classify things. The models compared include custom ResNet50, RNN (ICNA-CNN + LSTM), InceptionResNetV2, EfficientNetV2, and the proposed-VGG16. The proposed VGG16 model presents the best overall efficiency with the highest precision (99.07), F1 score (99.20%), and balanced low error rates (FNR: 0.6951%; FPR: 0.2694%). This indicates a strong generalization capability and minimal misclassification.

Table 3. Comparing the performance of our proposed models

Name of the model	Accuracy %	Precision %	Recall %	F1-Score %	FNR %	FPR %
Custom ResNet50	90.58	90.57	89.11	89.84	10.887	8.127
RNN (ICNA-CNN + LSTM)	93.40	93.25	92.47	92.86	7.531	5.797
InceptionResNetV2	97.98	97.09	99.50	98.28	0.4975	0.411
EfficientNetV2	98.27	99.01	98.04	98.52	0.9608	0.4085
Proposed-VGG16	99.07	99.10	99.30	99.20	0.6951	0.2694

Figure 7 distinctly demonstrates that the proposed VGG16 model is the best option for real-world application because it is more accurate and reliable than all the others. Models such as EfficientNetV2 and InceptionResNetV2 also present strong potential, while custom ResNet50 might need further optimization. Now, Figure 8 shows us what's going on inside. There are four line plots that show how the proposed model works throughout 100 training cycles. These plots show accuracy, loss, precision, and recall along the way.

Finally, Figure 9 shows the ROC curves for five different deep learning models. Once more, the proposed VGG-16 model stands out, with its curve running near the top-left corner—a clear indicator of its strong performance in classifying objects.

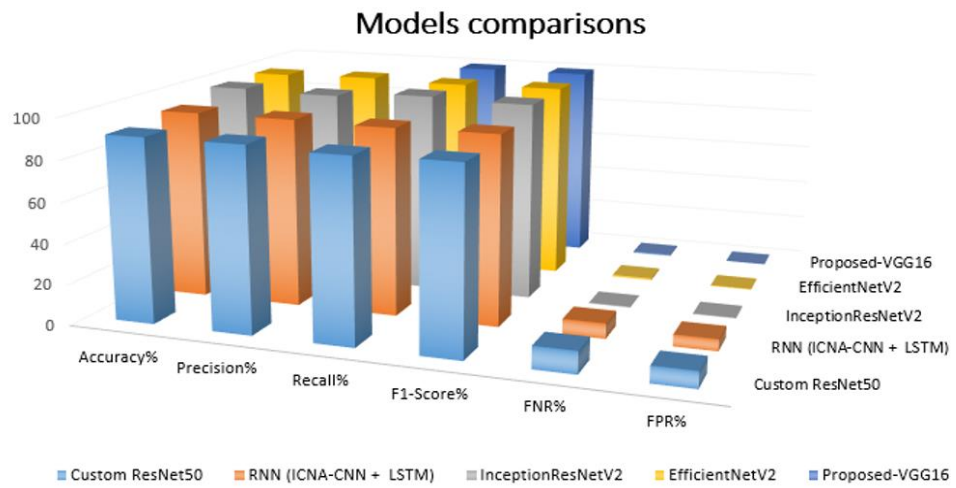

Figure 7. Present a comparison between the proposed model and with other exiting models

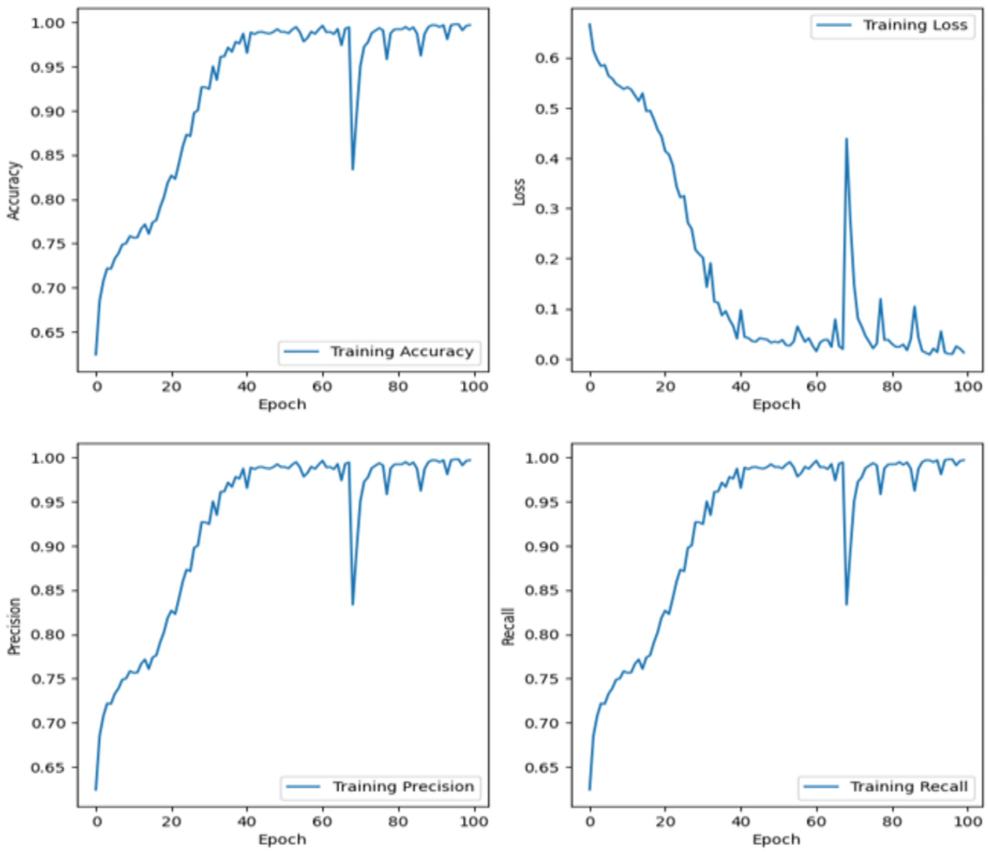

Figure 8. Proposed model convergence curve

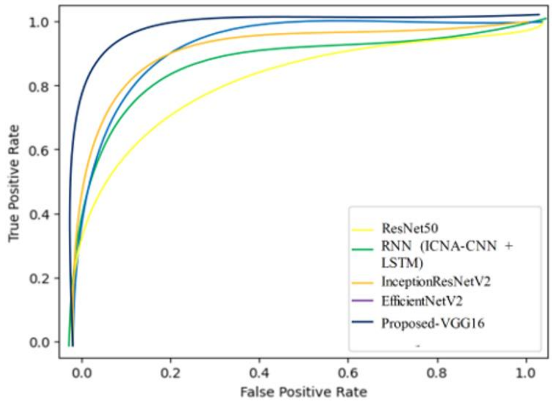

Figure 9. Comparison of ROC curve—proposed model and the tested models

6. CONCLUSION

In conclusion, this research offers a solid basis for wheat-weed classification utilizing agricultural imaging data that is based on DL. We developed and evaluate five distinct models to determine the most effective one for identifying weeds in wheat fields: EfficientNetV2, VGG16, a customized ResNet50, a hybrid RNN incorporate ICNA-CNN with LSTM, and InceptionResNetV2. To enhance image quality and ensure more robust feature extraction, a thorough preprocessing workflow was implemented. This pipeline involved several steps, including converting images from grayscale to RGB, resizing, normalization, contrast stretching, histogram equalization, and data augmentation. Among all the architectures evaluated, our VGG16-based model achieved a training accuracy of 99.07%, with precision and recall both reaching identical levels-outperforming every other model. This study contributes to the growing body of knowledge on how deep learning can support improved decision-making in precision agriculture. The ultimate aim is to maximize crop productivity while minimizing pesticide application and promoting eco-friendly farming techniques.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Seema Verma												✓		
Aishwary Bodhale		✓	✓			✓	✓	✓	✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors affirm that the work described in this publication was not impacted by any known competing financial interests or personal relationships. The authors also affirm that this paper is free of any non-financial conflicting interests, such as those that are academic, intellectual, religious, political, or personal. No conflicts of interest are disclosed by the authors.

DATA AVAILABILITY

The primary data used in this study was gathered straight from wheat fields. As part of the field experiments carried out for this study, the writers created and documented the data. The associated author can provide the dataset upon reasonable request.

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