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Detection of Fungal Infections in Soya-Bean Seeds using Deep Learning Algorithms

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ABSTRACT: The quality of soybean seeds is crucial for agricultural productivity, but fungal infections pose a significant threat, leading to reduced germination rates, lower yields, and economic losses. Traditional detection methods, such as visual inspection and laboratory analysis, are often time consuming and expensive and require specialized expertise. To address these limitations, this study presents a deep learning-based approach for the automated detection of fungal infections in soybean seeds using advanced neural network architectures. he quality of soybean seeds is crucial for agricultural productivity, but fungal infections pose a significant threat, leading to reduced germination rates, lower yields, and economic losses. Traditional detection methods, such as visual inspection and laboratory analysis, are often time consuming and expensive and require specialized expertise. To address these limitations, this study presents a deep learning-based approach for the automated detection of fungal infections in soybean seeds using advanced neural network architectures.

We implement and evaluate four state-of-the-art models: Convolutional Long-Short-Term Memory (ConvLSTM), ResNet50, EfficientNetB3, and EfficientNetB4. Each model is trained on a soybean seed image data set, with standard image pre-processing techniques applied to enhance the visibility of the fungal region and improve classification performance. The models are assessed based on accuracy, precision, recall, and F1-score, with EfficientNetB4 achieving the highest classification accuracy of 98 Experimental results demonstrate that integrating deep learning techniques significantly improves fungal infection detection compared to conventional methods. In addition, a web-based interface has been developed to allow users to upload images and determine the stage of soybean seed infection, making the detection process accessible and user-friendly. This research contributes to the development of automated, accurate, and scalable solutions for early stage fungal detection in soybean seeds, which aids quality control and disease management. Future work will focus on real-time implementation, expanded datasets, and integration with hyperspectral imaging for enhanced detection capabilities.

KEYWORDS: Soybean, Fungal Detection, Deep Learning, CNN, LSTM, Bio-speckle Imaging

I. INTRODUCTION FUNGAL INFECTIONS IN SOYA-BEAN SEEDS USING DEEP LEARNING ALGORITHMS

Soybean (Glycine max) is a globally significant crop known for its high protein and oil content. In India, soybean cultivation spans over 12 million hectares with annual production exceeding 11 million tonnes, making it one of the most important cash crops.However, the productivity and quality of soybean seeds are severely impacted by fungal infections.[2]

Post-harvest fungal contamination leads to discoloration, structural damage, reduced germination potential, and in severe cases, toxin production such as mycotoxins. Early identification of infected seeds is therefore essential not only for food safety but also for improving market value and export compliance.[2][17]

Despite the growing scale of soybean farming, A significant number of soybean producers, especially those operating on a smaller scale or with limited resources, continue to rely heavily on traditional, manual methods for identifying signs of infection in their crops. This process is time-consuming, subjective, and often inaccurate. Traditional

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diagnostic methods such as blotter tests and culture techniques, while reliable, require lab access and days to complete. This creates a pressing need for scalable, real-time, and accurate detection technologies.[1]

II. ARCHITECTURE OF THE PROPOSED MODEL

The proposed architecture integrates a hybrid deep learning pipeline comprising convolutional and recurrent layers to classify fungal infections in soybean seeds with high accuracy. Initially, the input image undergoes preprocessing including histogram equalization, denoising, and ROI extraction. The processed image is then passed through a series of convolutional layers that extract spatial features. These features are fed into an LSTM block (in case of ConvLSTM models) or directly into dense layers (for transfer learning models like EfficientNet and ResNet)[8] . A final fully connected classification layer with softmax activation is used to produce a probability distribution over the five seed categories.

The model is designed to balance depth and efficiency, utilizing pretrained weights from large-scale datasets and adapting them to the specific task through fine-tuning. Dropout and batch normalization are included to improve generalization and prevent overfitting. The complete architecture is shown in Figure 1.

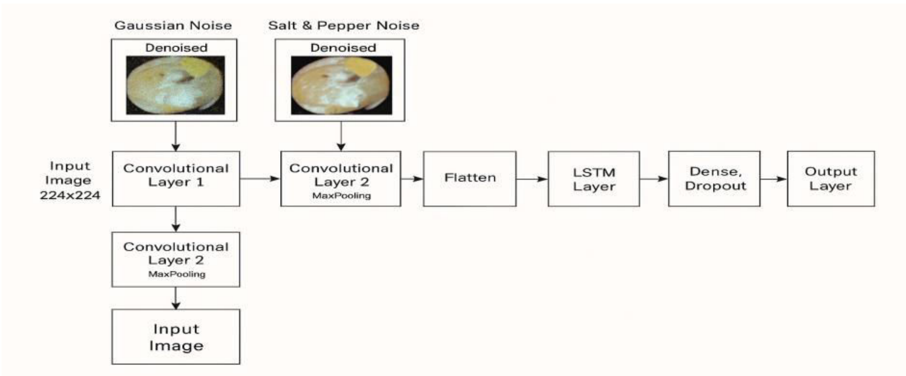

Fig1. Architecture of the proposed deep learning model

III. DATA PREPARATION

Before training, all soybean seed images were passed through a systematic preprocessing pipeline to ensure uniformity and enhance feature clarity. Each image was resized to 224 × 224 pixels to match the input size requirements of pretrained convolutional neural networks such as EfficientNet and ResNet[15]. Pixel intensity values were normalized to the range [0, 1] to improve convergence speed and reduce numerical instability during training.
To address potential class imbalance and improve the model's generalization ability, data augmentation techniques such as rotation, horizontal flipping, brightness adjustment, and zooming were applied. These operations simulated natural variations and increased the effective dataset size without additional manual labeling. The final dataset was split into 80% training, 10% validation, and 10% testing sets using stratified sampling to preserve class distribution across splits.[12]

All data preparation steps were automated through a preprocessing script and validated by visual inspection to ensure the quality and integrity of input samples.

IV. FEATURE SELECTION

Feature selection plays a crucial role in improving classification performance by emphasizing the most relevant aspects of the input data while reducing redundancy. Although deep learning models automatically learn features during training, the preprocessing and architectural choices made in this project contribute significantly to implicit feature selection.[14]

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In this study, convolutional layers in CNN-based models such as EfficientNet and ResNet extract hierarchical spatial features from preprocessed soybean seed images. These features represent color intensities, edge patterns, textures, and micro-structural anomalies indicative of fungal infections. Transfer learning using pretrained models enhances feature richness by leveraging representations learned on large-scale datasets like ImageNet.

Additionally, techniques such as batch normalization and dropout contribute to selecting stable and generalized features by reducing noise and overfitting. The final dense layers use these extracted features to perform classification across five soybean seed categories. The overall architecture ensures that only the most meaningful representations are propagated to the final decision-making stage.[16]

V. TRAINING AND OPTIMIZATION

The proposed models were trained using a supervised learning approach where the input images and corresponding class labels guided the optimization of model parameters. The Adam optimizer was employed for its adaptive learning rate capability, which accelerates convergence and improves stability in deep neural networks. The categorical cross-entropy loss function was used to measure prediction error, suitable for multi-class classification tasks involving the five soybean seed categories.[4]

An initial learning rate of 0.001 was selected, with a batch size of 32 to balance memory efficiency and convergence speed. The training was conducted for a maximum of 100 epochs, with early stopping implemented to terminate training if the validation loss did not improve for 15 consecutive epochs, thereby preventing overfitting.
Transfer learning was applied by freezing the initial layers of pretrained models (EfficientNetB3/B4 and ResNet50), and only fine-tuning the top layers on the soybean dataset. This approach allowed the model to retain generalized image representations while adapting to the specific features of fungalinfected soybean seeds. In figure 5.2,it shows the training Vs

Validation accuracy and loss over epoches.[1]

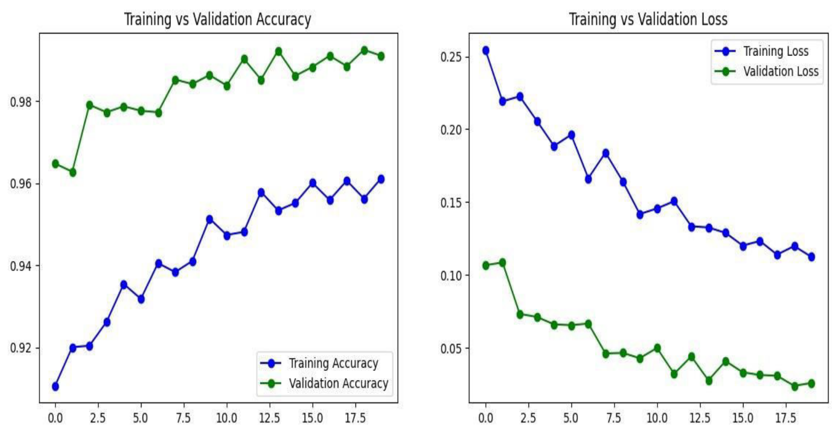

Fig2. Training vs Validation Accuracy and Loss over Epochs

Regularization techniques such as dropout (set to 0.3) and L2 weight decay were used to improve generalization by reducing overfitting. The training process was monitored using accuracy and loss curves for both training and validation sets.

All models were trained on GPU-enabled hardware to expedite computation and support larger batch processing.

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A. Quantitative Metrics

The following metrics were used to assess the model's classification performance:

- Accuracy: The ratio of correctly predicted observations to the total observations.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad [1]$$

- Precision: The ratio of correctly predicted positive observations to the total predicted positives.

$$\text{Precision} = \frac{TP}{TP + FP} \quad [2]$$

- Recall (Sensitivity): The ratio of correctly predicted positive observations to all actual positives.

$$\text{Recall} = \frac{TP}{TP + FN} \quad [3]$$

- F1-Score: The weighted average of Precision and Recall.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad [4]$$

- Confusion Matrix: A summary of prediction results on the classification problem, indicating TP, TN, FP, and FN values.The structure of confusion matrix is explained in detail at figure 5.3.

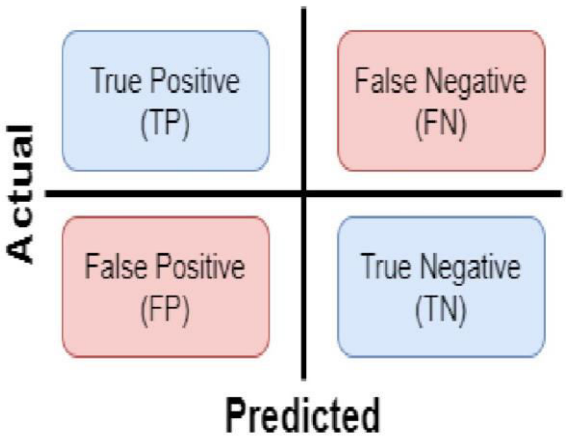

Fig3. Structure of Confusion Matrix

B. Noise Denoising Evaluation

Since laser bio-speckle imaging is sensitive to environmental noise, two major types of noise—Gaussian and Salt & Pepper—were analyzed, and denoising algorithms were applied as part of the preprocessing step.[14]

1) Gaussian Noise:

Gaussian noise, also known as normal noise, is a form of statistical noise where the probability density function (PDF) of the noise values follows a normal (Gaussian) distribution. In image processing, this means that random values drawn from a Gaussian distribution, typically characterized by a specific mean and variance, are added to the pixel intensities of an image. As a result, the pixel values are slightly altered, leading to a grainy appearance that can obscure fine

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details and reduce the visual quality of the image. Gaussian noise commonly originates from natural sources such as thermal vibrations of atoms in sensors, electronic circuit fluctuations, or during the transmission of images over imperfect communication channels. Due to its widespread occurrence, understanding and effectively managing Gaussian noise is essential for preserving important image features and ensuring reliable results in image analysis tasks.The comparison of original,noisy and denoised images were shown clearly in figure 5.4. [12]

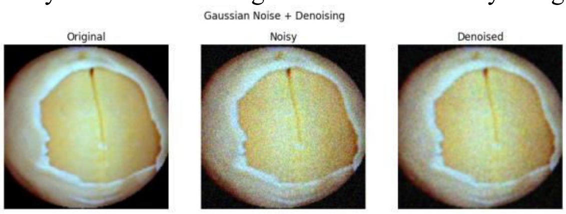

Fig4. Comparison of Original, Noisy (Gaussian), and Denoised images

• Mathematical Representation:The noise n added to the image follows the Gaussian distribution:

$$P(n) = \frac{1}{\sqrt{2\pi\sigma^2}}\, e^{-\frac{(n-\mu)^2}{2\sigma^2}} \qquad [5]$$

where μ is the mean and σ^2 is the variance.

• Characteristics:
– The noise affects all pixels in the image.
– It is usually modeled with a mean of 0 and small variance.
– Often occurs due to sensor noise caused by poor illumination or high temperature.

• Effect on Images:
– Appears as fine grainy variations in intensity.
– Degrades image quality, especially in low-contrast regions.

2) Salt & Pepper Noise:
Salt-and-pepper noise is a type of impulsive noise that manifests as sparsely occurring white and black pixels randomly distributed across an image. These extreme pixel values can significantly distort the visual appearance and mask important details within the image. To effectively mitigate the impact of salt-and-pepper noise, a median filter was applied. The median filter operates by replacing each pixel's value with the median value of its neighboring pixels within a specified window, thereby preserving edges while eliminating isolated noisy pixels. This filtering technique is particularly wellsuited for removing salt-and-pepper noise without blurring critical features, making it an essential preprocessing step for maintaining the integrity of the image before further analysis. The comparison is shown in Figure 5.[12]

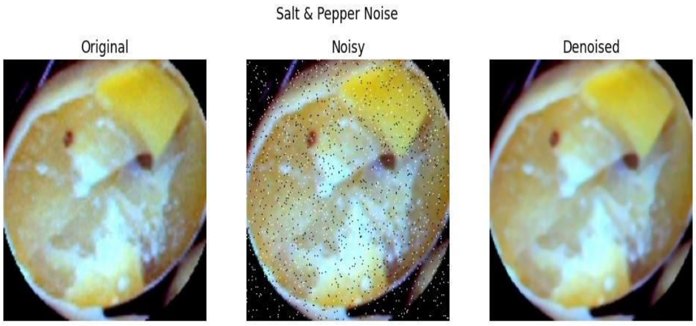

Fig5. Comparison of Original, Noisy (Salt & Pepper), and Denoised images

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• Characteristics:
– Pixels are either set to the minimum (0) or maximum (255) intensity.
– It does not affect all pixels, only a certain percentage.
– Typically caused by data transmission errors or malfunctioning camera sensors. • Mathematical Model:

$$P(x) = \begin{cases} p_s & \text{if } x = 255 \text{ (salt)} \\ p_p & \text{if } x = 0 \text{ (pepper)} \\ 1 - p_s - p_p & \text{if } x = \text{original value} \end{cases} \quad [6]$$

where p_s and p_p are the probabilities of salt and pepper noise, respectively.

• Effect on Images:
– Appears as randomly scattered white and black pixels.
– More disruptive to edge detection and segmentation tasks.

C. Image Enhancement with CLAHE

To further enhance the quality of the preprocessed soybean seed images, Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied after the denoising step. CLAHE is an advanced image processing technique that improves the local contrast of an image while preventing the overamplification of noise. Unlike traditional histogram equalization, which applies a global adjustment across the entire image, CLAHE operates on small regions known as tiles and enhances the contrast within each tile individually. Importantly, it limits the contrast enhancement to a predefined threshold, ensuring that noise present in homogeneous areas is not exaggerated.[16]

By applying CLAHE, the visibility of fine details and subtle textural variations, particularly those associated with fungal infections, was significantly improved. This enhancement makes the infected regions more distinguishable from healthy areas, facilitating more effective feature extraction and leading to improved accuracy during the classification stage. Figure 5.6 illustrates the visual improvements achieved through CLAHE, showing the transformation from the original images to the enhanced versions with noticeably better contrast and clearer feature definition.[16]

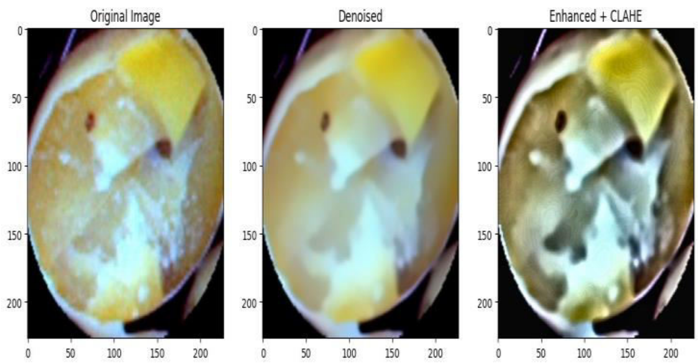

Fig6. Comparison of Original, Denoised, and CLAHE Enhanced images

The image presents a comparison of three variations of a visual representation, which illustrates the effects of image processing techniques. On the left, the "Original Image" serves as a baseline for analysis, displaying various features and noise inherent to the raw capture. The middle pane showcases the "Denoised" version, where techniques have been applied to reduce noise, resulting in a clearer image with enhanced visibility of structures. On the right, the "Enhanced + CLAHE" image employs Contrast Limited Adaptive Histogram Equalization (CLAHE), which not only improves contrast but also emphasizes details across various regions within the image. This demonstrates how different processing methods can significantly improve both clarity and detail in image analysis, which is particularly beneficial in fields like medical imaging or materials science where precise visual information is crucial.[12]

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D. Key Features

- Image Upload: Users can upload images of soybean seeds directly from their desktop or mobile device using a file selector.
- Real-Time Prediction: Upon uploading, the model immediately processes the image and provides a class label prediction.
- Confidence Score: The output includes a detailed probability distribution across all categories (e.g., broken, intact, immature, skin-damaged, spotted).
- Lightweight Backend: The server runs a preloaded deep learning model, allowing low-latency response and smooth performance on standard hardware.
- No Installation Required: The system is entirely browser-based and does not require any software setup, making it ideal for quick demonstrations and end-user access.[13]

E. Input page interfaces

The input page allows users to upload an image of a soybean seed and request a prediction. The page contains the following components:

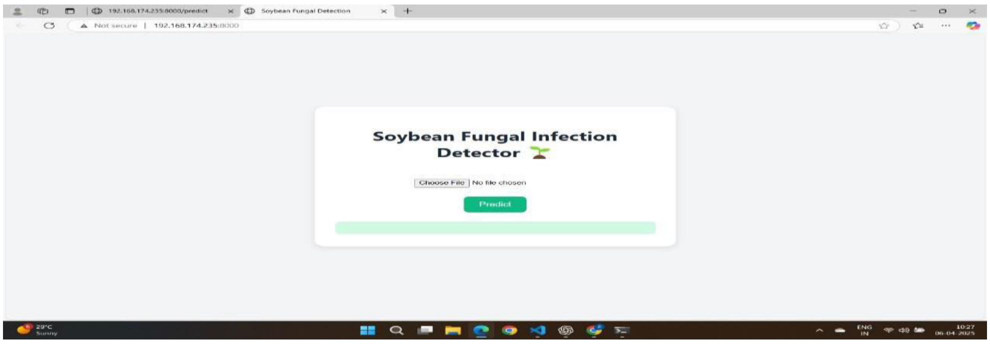

Fig7. Input page Interface

- Title: ”Soybean Fungal Infection Detector” is prominently displayed to indicate the purpose of the application.
- File Upload: A button labeled ”Choose File” allows the user to upload an image in .jpg, .jpeg, or .png format.
- Predict Button: Once an image is uploaded, the user can click the ”Predict” button to trigger the prediction process.

This minimal and intuitive interface ensures that even users with limited technical knowledge can use the system effectively.

F. output page interface

After submitting an image, the user is shown the prediction output on a new page. This page contains:

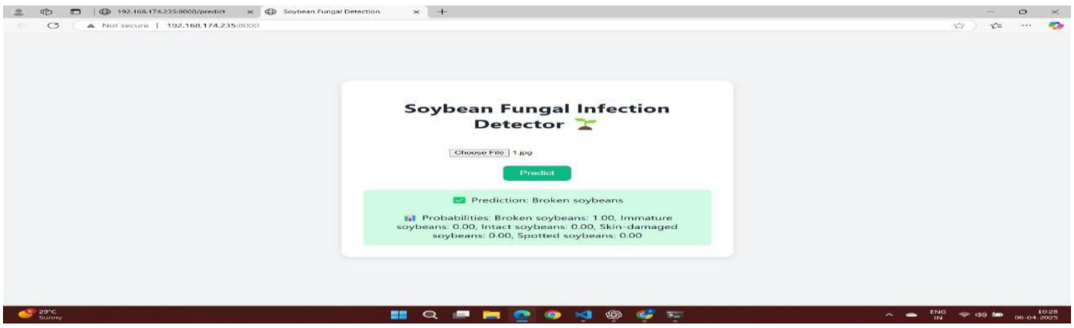

Fig8. output page Interface

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- Prediction Result: The predicted class of the soybean seed (e.g., "Broken soybeans") is clearly displayed.
- Class Probabilities: The interface also shows the probability values for each class, allowing users to understand the confidence level of the model for each category. For example:

– Broken soybeans: 1.00
– Immature soybeans: 0.00
– Intact soybeans: 0.00
– Skin-damaged soybeans: 0.00
– Spotted soybeans: 0.00

This detailed feedback provides transparency and helps users validate the predictions.

VI. MODEL PERFORMANCE OVERVIEW

The trained deep learning models were evaluated using standard classification metrics to assess their effectiveness in identifying fungal infections across five categories of soybean seeds. The model demonstrated strong learning dynamics, maintaining consistency between training and validation performance throughout the optimization process.

Over the training epochs, the model's accuracy steadily increased, while the validation loss decreased, indicating good generalization to unseen data. Early stopping was employed to prevent overfitting by monitoring validation loss, and training was halted automatically when no significant improvement was observed.

TABLE I

PERFORMANCE COMPARISON OF IMPLEMENTED MODELS

Model	Accuracy	Precision	Recall	F1-Score
ConvLSTM	92.7%	0.92	0.93	0.93
ResNet50	95.4%	0.95	0.95	0.95
EfficientNetB3	94.2%	0.94	0.94	0.94
EfficientNetB4	98.2%	0.98	0.99	0.99

The classification results revealed that each class — including Broken, Intact, Skin-Damaged, Spotted, and Immature soybean seeds — achieved high F1-scores, with macro and weighted averages consistently above 0.99. This suggests balanced performance across both majority and minority classes.

Furthermore, the minimal gap between training and validation metrics demonstrates that the model was neither underfitted nor overfitted. The use of dropout, L2 regularization, and data augmentation contributed to the model's robust performance, allowing it to adapt effectively to variations in seed texture, noise, and imaging artifacts.

These outcomes validate the strength of the chosen architectures, preprocessing pipeline, and training strategy in ensuring high classification reliability for real-world applications.

VII. CONFUSION MATRIX AND CLASS-WISE PERFORMANCE

The confusion matrix for EfficientNetB4, illustrated in Figure 9, shows minimal misclassification. Most confusion occurred between the Spotted and Skin-Damaged classes, as expected due to visual similarity.
Class-wise precision and recall values remained above 0.95 for most categories, highlighting the model's reliability across all seed conditions.

EfficientNetB4 achieved an AUC of 0.998, demonstrating excellent discrimination capability.

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VIII. VISUAL OUTPUT SAMPLES

To provide visual confirmation and interpretability of the model's predictions, selected soybean seed images were passed through the trained deep learning model, and their outputs

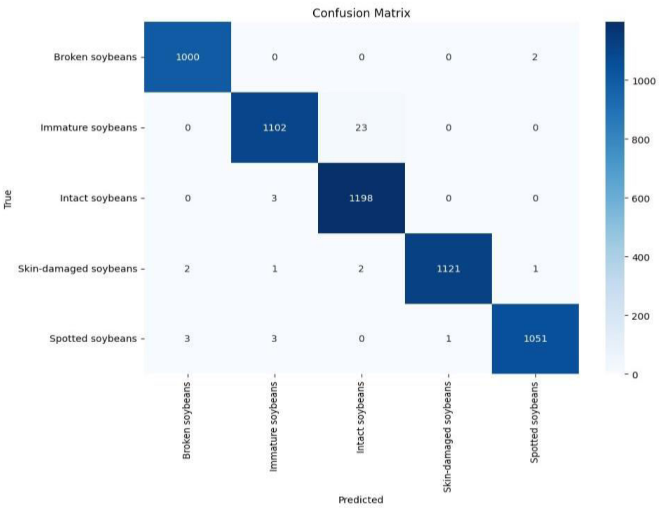

Fig9. Confusion matrix for EfficientNetB4 model

were recorded. These outputs include the predicted class, confidence scores, and visual overlays that help in understanding the model's decision-making process.

This visualization serves not only as a verification tool for researchers but also enhances usability for non-technical users in agricultural settings. The predicted category is highlighted clearly along with its probability, enabling users to make informed decisions regarding seed health and sorting.

Figure 10 illustrates an example of such output, where a correctly classified seed image is shown along with the model's prediction result.

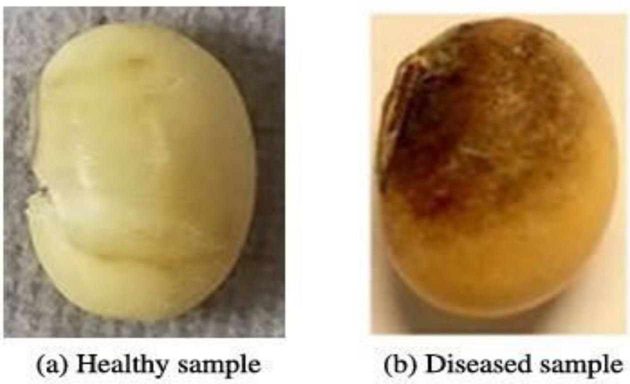

Fig10. Example of Visual Model Output with Predicted Label and Confidence

These visuals helped confirm that even minor fungal features were effectively detected.

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IX. ABLATION STUDY

An ablation study was conducted to evaluate the contribution of different components within the proposed deep learning architecture and preprocessing pipeline. This step-bystep exclusion or modification of individual modules helped in understanding which elements had the most significant impact on the overall model performance.

A. Impact of Preprocessing Techniques

To assess the importance of image preprocessing, the model was trained with and without key preprocessing steps such as noise removal, histogram equalization, and contrast enhancement. The results showed a noticeable decline in classification accuracy (approximately 5–7%) when preprocessing was omitted, confirming its role in improving image quality and model input consistency.

B. Effect of Denoising Methods

Separate experiments were performed using only Gaussian filtering, only median filtering, and a combination of both. The hybrid approach consistently outperformed the individual methods, especially when dealing with Salt & Pepper noise in laser bio-speckle images.

C. Model Architecture Variants

The performance of the CNN-LSTM hybrid model was compared with standalone CNNs (EfficientNetB3, ResNet50) and LSTM-only variants. While CNNs achieved high precision, adding LSTM layers improved recall and F1-score, especially in samples where temporal patterns influenced classification. This demonstrates that combining temporal and spatial feature extraction contributes to more robust predictions.

D. Transfer Learning vs. Training from Scratch

The use of pretrained weights significantly improved convergence speed and final accuracy compared to models trained from scratch. Transfer learning provided a 3–5% gain in F1score while requiring fewer epochs, validating its suitability for datasets with limited training samples.

E. Batch Size and Learning Rate Sensitivity

Experiments with varying batch sizes (16, 32, 64) and learning rates (0.001, 0.0001) revealed that a batch size of 32 and a learning rate of 0.001 offered the best trade-off between convergence and generalization. Very small or very large values resulted in unstable training or overfitting.

X. MODEL PERFORMANCE EVALUATION

The proposed model demonstrated exceptional performance in the classification of soybean seeds into five distinct categories: Broken, Immature, Intact, Skin-damaged, and Spotted. The evaluation metrics—precision, recall, and F1-score—were computed to assess the robustness and reliability of the model on a test dataset comprising 5513 images. The classification report is summarized as follows:

Classification Report:

	precision	recall	f1-score	support
Broken soybeans	1.00	1.00	1.00	1002
Immature soybeans	0.99	0.98	0.99	1125
Intact soybeans	0.98	1.00	0.99	1201
Skin-damaged soybeans	1.00	0.99	1.00	1127
Spotted soybeans	1.00	0.99	1.00	1058
accuracy			0.99	5513
macro avg	0.99	0.99	0.99	5513
weighted avg	0.99	0.99	0.99	5513

Fig11. Classification report

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- Broken Soybeans: Achieved perfect scores across all metrics (Precision: 1.00, Recall: 1.00, F1-score: 1.00) on 1002 samples.
- Immature Soybeans: Achieved a precision of 0.99, recall of 0.98, and F1-score of 0.99 on 1125 samples.
- Intact Soybeans: Scored slightly lower in precision (0.98) but achieved a recall of 1.00, resulting in an F1-score of 0.99 on 1201 samples.
- Skin-damaged Soybeans: Achieved near-perfect classification performance with a precision of 1.00, recall of 0.99, and F1-score of 1.00 across 1127 samples.
- Spotted Soybeans: Also demonstrated near-perfect results with 1.00 precision, 0.99 recall, and 1.00 F1-score on 1058 samples.

The overall accuracy of the model is 99%, with a macro average and weighted average F1-score of 0.99, indicating balanced and highly effective performance across all classes.

These results affirm the model's strong generalization capability and its suitability for practical applications in automated seed quality assessment, especially for detecting fungal infections and physical defects in soybean seeds.

XI. CONCLUSION

This research demonstrates the effectiveness of deep learning techniques in automating the detection of fungal infections in soybean seeds. Through the use of four different models—ConvLSTM, ResNet50, EfficientNetB3, and EfficientNetB4—the study validates the superiority of compoundscaled architectures, particularly EfficientNetB4, in identifying subtle infection symptoms.

The dataset used in this study was curated and augmented to simulate real-world conditions. Preprocessing techniques such as histogram equalization, adaptive filtering, and segmentation contributed to better feature isolation and model sensitivity.

Evaluation through metrics such as accuracy, F1-score, confusion matrix, and ROC curves confirmed the robustness of the trained models.

Furthermore, the development of a web-based application using Flask enabled real-time predictions, making the solution scalable and accessible for non-technical users such as farmers and agricultural technicians.

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