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Research

Evaluating AI-Based Methods for Sugarcane Leaf Disease Detection and Classification using Image Processing Techniques

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Abstract:
The health of sugarcane crops is fundamentally significant for the rural economy, yet they are habitually compromised by different leaf illnesses that can altogether decrease yield and quality. Powerful and opportune location and arrangement of these sicknesses are fundamental for carrying out suitable administration methodologies. A comprehensive comparison of various artificial intelligence (AI) methods for identifying and classifying sugarcane leaf diseases is presented in this study. Leaf diseases impact food security and profitability by lowering agricultural output and quality. In most country India, agribusiness is the principal kind of revenue. Consequently, farming plant infections should be naturally analyzed and arranged utilizing exceptional and exact man-made intelligence (Computerized reasoning) strategies. This permits ideal preventive counsel. Image processing, Machine Learning, and Deep Learning are utilized in AI strategies. The most recent studies on sugarcane leaf disease detection and classification were thoroughly examined. The investigation centers around DL or ML calculations, explore datasets, execution pointers, and model precision. SVM (Support Vector Machine) was used in 45 percent of sugarcane leaf image classification studies, while KNN (K-Nearest Neighbors) was used in 22%. In 22% of queries, K-means clustering and ANN (Artificial Neural Network) classifiers were utilized. Pre-trained models were used in 44% of studies, while CNN (Convolutional Neural Network) models were used in 56%. When compared to controlled laboratory images, the performance of machine learning and deep learning models on real-world image datasets is subpar. Deep learning models, on the other hand, were 98.84 percent more accurate than machine learning models. Image categorization with ML models is inferior. Prior research's detection and classification techniques had significant flaws. New crop disease diagnosis and plant leaf disease detection and classification methods will be discovered thanks to this study.

Keywords: *Artificial Intelligence, Machine Learning, Deep Learning, Plant Leaf Disease Detection, Precision Agriculture, Crop Management.*

I. INTRODUCTION

The agricultural sector faces significant challenges due to the prevalence of diseases that affect crop health and yield, with sugarcane being a crucial crop subject to various leaf diseases. Early detection and accurate classification of these diseases are vital for effective disease management and ensuring optimal crop production. Traditional methods of disease detection, which rely on manual inspection, are time-consuming and often inaccurate due to human error. In recent years, artificial intelligence (AI) has emerged as a powerful tool in agriculture, offering innovative solutions for automated disease detection and classification.India currently holds the title of being the most populous country in the world, with a share of 17.8% of the global population as of April 14th, 2023. [1]. According to the Food and Agriculture Organization of the (FAO) world will need 70% more food in 2050 to feed the population on Earth. Due increment in population will lead to the requirement for more food production [2]. India's economy is supported primarily by its agricultural sector. Crop disease/infection can lead to substantial reductions in both crop yields and quality. Early detection of diseases is a preventative action that can be taken in order to boost production and cut down on economic losses. In recent decades, eye contact has become the method that is most commonly employed for the diagnosis of disease [3]. On the other hand, this strategy is not suitable on a large scale because it requires extra time and there are no professionals available on the more remote farms [4]. Artificial Intelligence played a very important role in the development of methods for the detection and classification of plant diseases automatically by using advanced techniques. As a result of this, the development of tools for image analysis has become an efficient method for determining the state of a plant's health[5]. The analysis of the visible patterns on the photographs of the leaves can be used to make a diagnosis since illnesses leave a certain mark on plants, notably in the leaves[6]. The use of images in conjunction with the process of Machine Learning (a subfield of Artificial Intelligence) provides a solution to the problem of agricultural production and helps to ensure that there will always be food available [7].

Finding plant diseases is usually a difficult and time-consuming task. Fungi, bacteria, and viruses are the primary agents of infection that can be found in plants. It is possible for infections to manifest in any part of the plant, including the roots, leaves, and stems. Farmers are aware that the correct instruments for measuring and adjusting the required parameters for light, humidity, and temperature are necessary in order to acquire crops of higher quality and greater profitability [8]. Researchers are encouraged to hunt for fresh, resource-rich, and time-efficient inventions that can assist in increasing agricultural output [9][10]. With the naked eye alone, it can be challenging to reliably identify the various pathogens that can be found on the leaves of plants [8]. In addition to being of great use, the electronic system that professionals use to communicate with one another will be of great assistance in accurately analyzing data in a timely manner [11]. In recent years, research has been conducted to study alternative electronic methods that are both speedy and non-invasive in the diagnosis of Plant leaf disease[7].

The prevention and treatment of illnesses and pests can be aided by good agricultural practices. By employing particular cultures, one can cut back on the quantity of necessary medical treatment or costly procedures. Sensory technology, computer processing, remote sensing processing, robotics, and other information technologies are being utilized in today's agricultural farms. Accurate monitoring of agriculture is accomplished through the utilization of agricultural applications with precision (such as spraying only diseased regions), the identification of contaminated areas through the utilization of stationary stations, sensory networks, drones, and mobile robots, and the distribution of operators [12]. The only drawback of using these methods is the difficulty in locating specialists in the field. There is a need for either field experts or skilled farmers to utilize new prediction software, for better understanding the relationships between plants, pathogens, and their environments in order to make accurate predictions regarding crop yield. [4].

II. A Brief Overview of Deep Learning and Machine Learning

Machine Learning and Deep Learning are the most widely used AI-based techniques for developing models for the identification and categorization of plant leaf diseases. It's predicated on the possibility that PCs can independently dissect information, spot examples, and choose ends. This is the field of PCs to provides the capacity to learn and make their own rationale/code/choice, which will pursue PCs act and go with decisions like a human cerebrum. This only requires minimal human involvement and no explicit programming.

Automated learning and performance enhancement are the hallmarks of computers and machines alike. The qualities of the information that are promptly accessible and the necessities of the gig that should be done will figure out which calculation will be picked. Preparing assumes a urgent part in model's result, model prepared with wrong information can prompt adverse outcomes, choice of information and model for preparing is crucial[13].Machine learning (ML) systems, in general, involve two processes:

(a) Learning (for training)
(b) Testing.

These attributes often constitute a binary or numeric, ordinal, or nominal feature vector to aid in the former process. This vector serves as an input during the learning stage. In a nutshell, the machine learns experience doing the task by relying on a training dataset during the learning phase. The procedure is completed when the Machine's learning performance reaches a sufficient level (as expressed mathematically and statistically). The model that is developed during the training phase can then be used for clustering, classification, or prediction. Fig. 3 depicts a high-level outline of a typical machine-learning system. Pre-processing is required to convert the obtained complex raw data into a usable format. Typically, this includes:

(a) Data cleansing: The process of cleaning up data by removing noise and elements that are inconsistent or missing.
(b) Data integration: in situations where multiple data sources are available.

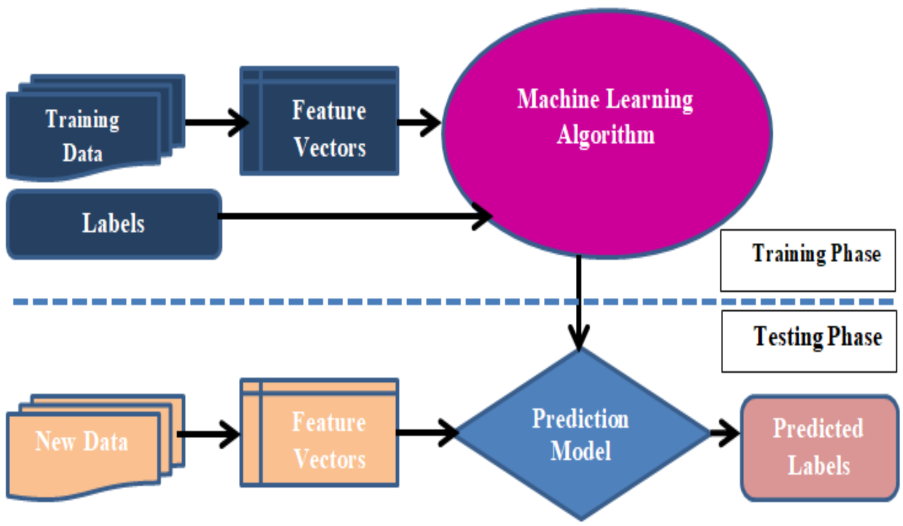

Figure. 1. **A graphical blueprint of a run of the mill AI System**

Deep learning (DL) is a part of AI (ML) that was at first evolved in 1943 by Walter Pitts and Warren McCulloch. The human brain's neural networks served as inspiration for their computer model. Edge rationale, a combination of calculations and science, was concocted to copy the mental cycles of the human psyche. This empowered PCs to reenact human points of view [14].

Fig. 2 portrays the progression of the profound growing experience. This means that the dataset is first gathered before being divided in half. Typically, training uses 80 percent of the dataset, while validation uses the remaining 20 percent. Thusly, you may either develop the profound gaining model all along or get the preparation/approval chart by utilizing move learning techniques to exhibit the viability of the model [16]. After that, the image is categorized according to the various plant diseases using output metrics, and then visualization and mapping techniques are used to find, locate, and classify photos [17].

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Figure. 2. Utilization of the Deep Learning Model

We gathered and examined a variety of current methods for diagnosing plant diseases that make use of deep learning and machine learning in this study. We additionally stressed the critical difficulties experienced. In any case, there are still a few irritating issues. The absence of true picture datasets, challenges in commenting on and yet again naming information for early illness recognition, exact distinguishing proof and extraction of contaminated regions and side effects when numerous sicknesses share comparative side effects, exact assessment of illness seriousness at different stages, and the productivity of the profound learning models that are right now being used are a portion of these impediments [8]. Therefore, in order to safeguard crops and detect diseases, thereby preventing potential issues, it is essential to employ cutting-edge techniques on actual images with exacting precision.

III. Causes for Infections and Normal Sugarcane Leaf Illnesses

To prevent sugarcane crops from suffering significant yield losses and to lessen the impact of these diseases, timely identification and appropriate management practices are essential. Different infections can happen at various phases of a plant's turn of events and adversely influence its development, at last prompting destructive consequences for by and large yield creation. Different elements impact the event of plant infections at different periods of plant development. Fig. 3 demonstrates that there are two primary categories of plant diseases: biotic variables and abiotic factors. Microbial contamination in plants prompts the improvement of biotic factors, for example, infections, growths, microorganisms, bugs, and slugs.

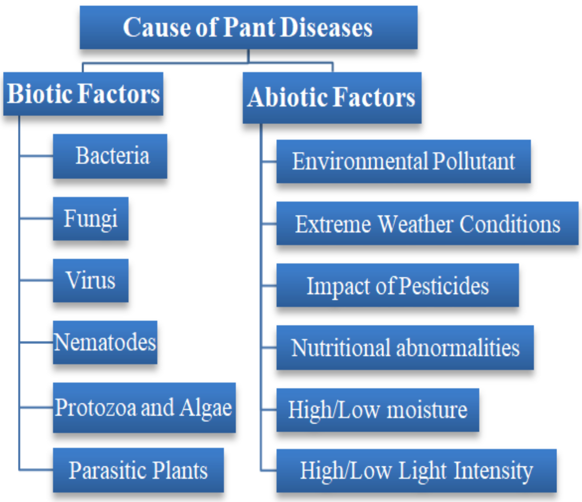

Figure. 3. Various causes of disease in plants

Leaf diseases in sugarcane pose a significant threat to sugarcane production because they affect the plant's overall health and reduce crop yield. Sugarcane leaves can be affected by a variety of fungal, bacterial, and viral diseases that frequently cause lesions, discoloration, wilting, and other visible signs.

Syndrome of the Yellow Leaf: Apparent through leaf yellowing, particularly along the midrib, frequently bringing about ensuing drying and shrinking, generally set off by viral contaminations.

Eyespot (Cercospora): Makes oval extended injuries with yellow radiances on leaves, later becoming rosy brown or dim brown, provoking untimely leaf drop.

Muck (Ustilago scitaminea): Symptoms include swollen, elongated, and dark gray spores on the leaves, which cause stunted growth.

Red Decay (Colletotrichum falcatum): characterized by internal cane rot and red discoloration in leaf vascular bundles.

Scald of the Leaf, Xanthomonas albilineans: exhibits brown, elongated, water-soaked lesions with yellow margins that are wilting.

Leaf Smear (Bipolaris sacchari): causes brown patches that are irregular and have water-soaked margins, causing significant damage to leaf tissues.

Ratoon Hindering Infection (RSD): Stunts development with yellowing, shortening, and limiting of leaves, influencing regrowth after gather.

Stick Mosaic Sickness: Shows mosaic examples on leaves, prompting hindered development and diminished plant force.

Fosarium moniliforme Pokkah Boeng: Shows white to grayish-green spots on leaves, advancing to brown with resulting shrinking and leaf demise.

IV. Literature Review

Sugarcane (genus: *Saccharum*) is a member of the family Poaceae. Brazil contributes the most, followed by India, Thailand, China, and the US in sugarcane production. The sugarcane crop is highly susceptible to various disorders like temperature fluctuations, diseases caused by bacterial fungal, viral agents, and pests. In terms of yield and juice quality, a conservative estimate of losses caused by diseases on the entire sugarcane production is about 10-25%.In this study, we looked at a number of modern algorithms that use artificial intelligence-based methods to identify and diagnose plant leaf diseases. We then divided the algorithms into two groups: machine learning and deep learning. While the following part offers a description of machine learning and deep learning methodologies, the first portion of the literature review offers a brief introduction to these approaches. Furthermore, we presented a tabular comparative analysis of the methods under investigation.

A. Techniques for identifying and classifying sugarcane leaf diseases based on machine learning

White leaf disease (WLD) was detected in the sugarcane field by Narmilan in [18]. The system also included various python libraries, vegetation indices, and 5 spectral bands in addition to decision tree (DT), random forest (RF), K-nearest neighbors (KNN), and XGBoost (XGB) ML techniques. At the point when it came to identifying WLD in the field, the KNN, RF, and XGB all figured out how to accomplish a precision pace of 94%. Ratnasari used a Help Vector Machine classifier that integrates the L∗a∗b∗ variety space for variety credits and the Dark Level Co-Event Lattice for surface qualities. This proposed model has the ability to exactly distinguish the different types of spot sicknesses with a degree of precision coming to 80%. [19]. The system was successfully validated by the researchers using Paguiruan Floridablanca Pampanga samples. The device-categorized leaf samples were also checked by the Research Science Specialist. The Disarray Network was used to assess the exactness of the framework's arrangement for yellow spot sickness. Based on the matrix computation, the researchers met their initial goal of exceeding 80 percent accuracy [20] with an accuracy of 86.67 percent. Another review distinguishes red decay, mosaic, and leaf burn sicknesses in sugarcane plants. The accuracy of these applications has been significantly improved by combining various classifiers and feature extractions like color, size, and shape. The leaf dataset was grouped utilizing the k-implies arrangement technique, bringing about a precision of 97% [21]. Digital images of sugarcane plants with symptoms of a specific disease were used by researchers. The K-Means and SVM algorithms were used to identify the affected areas and break them up into segments. GLCM (Dim Level Co-event Frameworks) highlights were gotten from each portioned locale and used as contributions for a classifier. Because not all features were anticipated to provide equal amounts of information about the target, researchers used cross-validation to identify the features that made up the most effective classification model. The ANN, linear, and non-linear SVM Classifiers had achieved accuracies of 85%, 91%, and 94%, respectively [22]. For Sugarcane Leaf Sear Illness, Leaf surface pictures are extricated from RGB pictures and switched over completely to a L*a*b variety model with most extreme quantization. Regardless of camera flash, leaf type, disease spot type, or background, color model L*a*b accurately detects disease. Better execution is accomplished with K-implies for dark scale pictures. The K-NN classifier is used to classify features with 95% accuracy [23]. Through image pre-processing, unwanted image data is suppressed and the diseased sugarcane leaves are acquired. AHE, or Adaptive Histogram Equalization, enhances the image. We then portion utilizing Versatile k-implies bunching. The favored highlights are separated utilizing PCA and GLCM and SVM groups illnesses. Six critical illnesses that influence sugarcane yield were tried utilizing GLCM, PCA, and SVM classifiers. The proposed framework had 95% precision [24].

TABLE 1: COMPARATIVE ANALYSIS OF ML BASED METHODS

Methods	Performance Metrics	Datasets	Accuracy (%)	Reference
XGB, RF KNN, DT over UAV images	Accuracy	Real field images	93%	[18]
SVM	Accuracy	Private	80%	[19]
SVM	Accuracy, Precision	Private	86.67%	[20]
K-Means Clustering	Accuracy	Private	97%	[21]
ANN, SVM	Accuracy	Private	85%,94%	[22]
KNN, Median Filtering, Otsu Method	Accuracy	Private	95%	[23]
Adaptive k-Means Clustering, GLCM, SVM	Accuracy	Private	95%	[24]

TABLE 2: HIGHEST LEVEL OF PRECISION ACHIEVED WITH VARIOUS ML CLASSIFIERS

Classifier Name	Accuracy Achieved (%)
ANN	85%
K-Means Clustering	97%
KNN	95%
SVM Linear	95%
SVM Non-Linear	91%

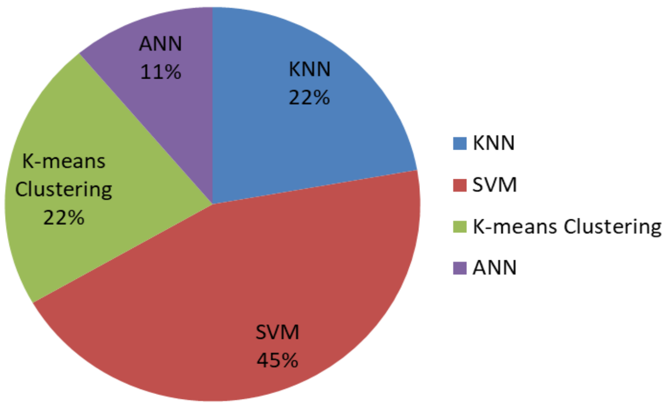

Figure. 4. Proportion of ML-based Classifier used.

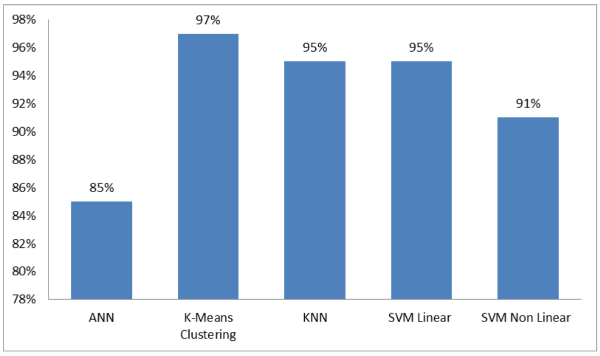

Figure. 5. ML-based classifier accuracy comparison

1) *Analysis of ML-based approaches*

Tables 1-2 and Fig. 4-5 provide a comprehensive analysis of machine learning, including discussions on parameters such as classifiers, datasets, and the highest accuracy achieved by different classifier classes. Table 1 provides a summary of the different datasets that researchers have examined to detect and classify Sugarcane leaf diseases using ML techniques. In the following section, we present a detailed analysis of the parameters in Table1. By examining Tables 1-2, we conducted a detailed analysis of various parameters, including the classifier type, the dataset employed in the study, and the maximum accuracy attained by the classifier. Based on this analysis of parameters, it can be inferred that the majority of the studies outlined in Table 1 have employed a private dataset for experimental objectives. The majority of machine learning approaches utilized Support Vector Machine (SVM) for classification in their models, analysis revealed that 45% of the machine learning-based sugarcane leaf image classification studies employed Support Vector Machines (SVM), while 22% of the studies utilized K-nearest Neighbor (KNN). Additionally, 22% of the studies employed K-means clustering, and 11% utilized Artificial Neural Network (ANN) classifiers. K-means Clustering classifier attained the highest accuracy i.e. 97%. The majority of ML-based classification methods employed private datasets for both training and testing. However, the private image dataset has a restricted size, which can potentially impact the training of the utilized model. Another concern regarding the image dataset is its scale or magnitude. The ML-based methods that incorporate segmentation/clustering as a pre-processing step exhibit significantly higher accuracy compared to other methods. Applying proper segmentation and other preprocessing techniques can greatly enhance the feature of input, thereby boosting the classifier's performance.

B. Deep Learning based Methods for Sugarcane leaf Sicknesses recognition and order

Upadhye and co According to [25], a straightforward CNN with discrete divisions into four classes can detect sugarcane diseases with an accuracy of 98.69 percent. As well as furnishing ranchers with direction, an online application has been produced for the identification of sugarcane crop illnesses. A SVMWEL (Support Vector Machine Weighted Average Learning) classifier was proposed by Vignesh and Chokkalingam in [26]. This classifier learns the extraction of image features and then divides them into six distinct categories based on those features. The suggested method's ability to diagnose illnesses in sugarcane plants is evaluated using metrics like precision, accuracy, the F-measure, and recall. When compared to the methods that are currently used in the industry, the experimental results show that the proposed method has a detection accuracy that is approximately 97.45 percent higher. Li et al. In [27], a lightweight vision transformer based on shuffle convolution was proposed that demonstrates that every change made to SLViT has improved its overall performance. 98.84 percent is its precision accuracy. On the Plant Village Dataset, SLViT outperforms six SOTA and three other custom-created leaf disease detection models. SLViT outperformed MobileNetV3_small on the private dataset SLD10k, improving accuracy by 1.87 percent and decreasing dataset size by 66.3%. SLViT likewise outflanked MobileNetV3_small. Additionally, the experiment demonstrates that SLViT has incorporated the advantages of the lightweight CNN and noise-resistant transformer into its design. This study demonstrates that SLViT can be utilized in the field to identify pathology in sugarcane leaves. Tamilvizhi et al. in [28] Introduced an imaginative method for profound exchange discovering that utilizes quantum-acted molecule swarm streamlining. An ideal algorithm for region segmentation will be developed as part of this method to reliably identify the affected areas in an image of a leaf. Additionally, the SqueezeNet model and the deep stacked auto encoder (DSAE) classification model are utilized for feature extraction. All in all, the QBPSO calculation is utilized to tweak the DSAE model's hyperparameters to accomplish ideal execution. The results of a wide range of tests ensured that the QBPSO-DTL model would be enhanced as a result of the improvements. This was done with the goal that the superior results of the QBPSO-DTL strategy could be illustrated. Malik and co. The effectiveness of this method in detecting intricate patterns and variations observed in real-world situations was demonstrated by the fact that in [29] achieved a notable accuracy of 73.40 percent for images from credible web sources and 93.20 percent for the test set. Yolo and Faster-RCNN object-detection algorithms were used to identify the affected regions. On their own datasets, both networks scored 58.13% mean average precision. CNNs on a large dataset would make automated disease recognition systems possible, taking everything into account. In [30], Manavalan gave an overview of a number of image processing and ML algorithms that are used to quickly extract features from sugarcane disease diagnoses. In addition, we investigate the problems and potential future developments associated with computational methods used to identify sugarcane diseases. Daphal and Koli in [31] Move learning frameworks can perform well with restricted datasets. VGG-16 Net and ResNet have 83.00% and 91.00% exactness, individually. In , the most cutting-edge deep learning techniques, such as neural networks and hybrid AdaBoost, are contrasted with Srivastava and others' SVM, ANN, symmetric gradient descent, naive Bayes network, and logistic regression. Different measurable computations, including exactness, accuracy, particularity, and awareness, are completed utilizing Orange programming. The scenario with the highest accuracy is selected as the best option. One procedure for deciding an estimation's exactness is to compute the beneficiary working trademark bend. The AUC of VGG-16 and SVM as component extractors and classifiers, individually, is 90.2 percent. CNN's Hyperspectral Double Self-Consideration Block (DSAB) identifies muck sickness in prior to the onset of side effects. Combining Resnet34 and DSAB resulted in an accuracy rate of 90.86% for the early detection of filth illness.

TABLE 3: COMPARATIVE ANALYSIS OF DL BASED METHODS

Methods	Performance Metrics	Datasets	Accuracy (%)	Reference
CNN	Accuracy	Real field images	98.69%	[25]
Ensemble learning Convolutional Support Vector Machine Weighted Average Ensemble Learning (EnC-SVMWEL)	Exactness, accuracy, review, and F-measure	Real field images	97.45%	[26]
CNN with Vision transformer	Precision	Plant Village and Self-Created	98.84%	[27]
QBPSO-DTL, CNN, DASE, SqueezeNet, Inception v3	Precision, Recall, F1-Score, Accuracy, AUC	Private	95.40%	[28]
CNN, YOLO, Faster R-CNN	Accuracy, Precision	Private, and Public Source	93.20%	[29]
CNN, DSAB, ResNet34	Accuracy, AUC, F1-Score	Private	90.86%	[33]
VGG-16 net, ResNet	accuracy, precision, specificity, AUC	Private	91%	[31]
Inception v3, VGG-16 and VGG-19	accuracy, precision, specificity, AUC,	Real field images	84.40%	[32]

Recall

Table 4: Highest accuracy achieved by various DL classifiers.

Classifier Name	Accuracy achieved (%)
CNN based model	98.84%
Pre-trained Model	95.40%

TABLE 5: DATASET DETAILS AND CONSTRAINTS FOR TOP 3 HIGHEST ACCURACY IN DL-BASED APPROACH

Performance metrics	Dataset	Accuracy (%)	No of images in dataset	No of Diseases	Reference
Precision	Plant Village for training and Self Created for testing	98.84%	2095	6 (down medow, ring spot, yellow spot, brown spot, red spot, brown strip)	[27]
Accuracy	Real field images	98.69%	580	4 (Wilt, rot, Grassy Shot, smut)	[25]
accuracy, precision, recall, and F-measure	Real field images	97.45%	2940	5 (Cercospora leaf spot, red rot, helminthosporium leaf spot, rust, and yellow leaf disease)	[26]

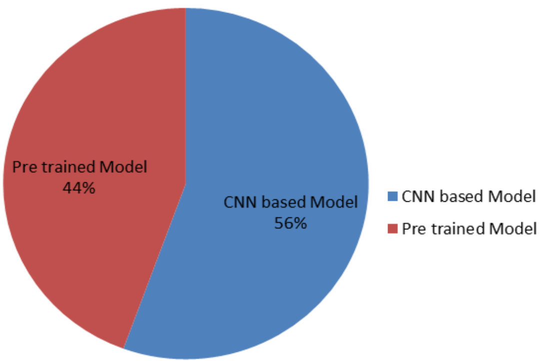

Figure. 6. Proportion of used DL Classifier

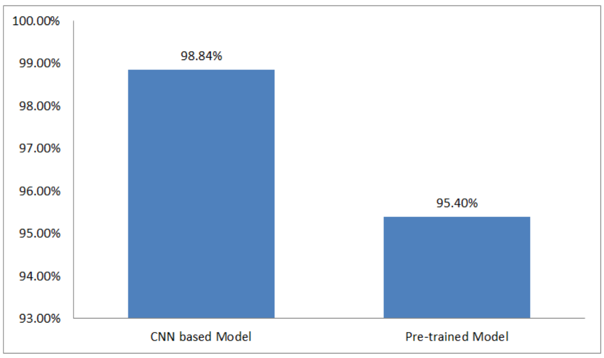

Figure. 7. Comparison of DL-based classifier accuracy

1) Analysis of Deep Learning Approaches

Table 3 provides a comprehensive analysis of deep learning-based studies, focusing on individual parameters. Based on this tabular data, we conducted a more in-depth analysis of the characteristics and types of classifiers, the specific datasets, and the maximum accuracy attained by various classifier categories. Most of the deep learning methods employed convolutional neural networks (CNNs) or CNN variants as their foundational models, as shown in Fig. 6, for the purpose of detecting and classifying Sugarcane leaf diseases using the Private dataset (refer to Table 3). The majority of the research summarized in Table 3 employed pre-trained deep learning models, resulting in an accuracy of 98.84% (as shown in Table 4). 44% of the studies used pre-trained Models and 56% of studies used Convolutional Neural Network (CNN) based models. Moreover, the models that employed image pre-processing techniques such as filtering, segmentation or contextual information integration to improve the distinction of the affected area in the image, or optimization for feature extraction and selection, exhibited markedly better performance in comparison to other models. It is worth noting that models using real-field images have a relatively low performance, as shown in Table 3. As less number of images are used in the dataset for DL-based approaches with a limited number of disease classes gives higher accuracy (see Table 5). Large number of images and classes can alter the performance and accuracy. When using deep learning models, there are two important factors to consider. Firstly, it is crucial to have a substantial dataset of relevant plant images in order to train the model effectively and ensure its ability to generalize to real-world images. Another consideration is the implementation of an image pre-processing or optimization algorithm to enhance the process of feature extraction and selection, enabling accurate detection and segmentation of the affected region in a sugarcane leaf image.

C. Key Difficulties in Distinguishing and Characterizing Sicknesses in Sugarcane Plant Leaves

- Following that, a complete and basic examination of different present day moves toward that utilize AI and profound learning for the point of perceiving and characterizing sicknesses found in sugarcane leaves, as portrayed in the past exploration distributed in the pertinent scholastic diaries. The ID and classification of sugarcane leaf illnesses present various critical difficulties, which we have talked about beneath. As a result, researchers will be able to investigate the aspects that have the potential to significantly affect real-time systems used to identify and diagnose leaf diseases. There are a lot of different things to take into account when classifying and identifying diseases. Coming up next is a complete rundown of these variables:
- Disease features, extraction, and classifier selection are critical to the success of plant disease detection systems [33].
- The type and quality of dataset utilized in training and testing highly impacts the classifier's performance [34].
- Identifying diseased areas in leaf imagery requires background removal and segmentation, as complex backgrounds can impact detection model performance in real-world settings [33].
- It is difficult to determine if a plant is infected or lacking minerals or nutrients [3].
- Early disease detection is crucial for plants as disease/infection can occur at any stage of development [36].
- The majority of symptoms associated with diseases lack distinct boundaries and instead merge with normal tissue, resulting in a challenging differentiation between healthy and diseased areas [37].
- Identifying and separating distinct diseases can be challenging due to their simultaneous manifestations, leading to hybrid symptoms (multiple diseases on one leaf).
- Optimal hyper-parameter selection and tuning can significantly impact performance [24].
- Uniform disease characteristics, infected regions, and selecting appropriate attributes present significant challenges for disease recognition systems [5].

V. Spectral-Histological Image Processing Approach for Sugarcane Leaf Disease Detection

The effective identification of pathological anomalies in sugarcane leaves can be achieved through advanced image processing techniques that mimic the precision of laboratory-based histological methods. This section introduces a spectral-histological hybrid technique, a method that merges spectral decomposition with cellular pattern analysis to isolate and detect disease signatures in digital images of leaf samples.

1. Spectral Decomposition using Modified Fourier-Band Fusion

Instead of using the usual RGB or HSV color methods, the proposed method uses multiband spectral decomposition by applying a Modified Fourier-Band Fusion (MFBF) algorithm. This approach separates a leaf image into its low-frequency (macro-structural) and high-frequency (micro-structural) components, which are then fused using a dynamic weight matrix derived from chlorophyll reflectance gradients.

- Low-frequency analysis highlights discoloration, wilting, or midrib bleaching.
- High-frequency analysis accentuates vein rupture, fungal rings, or bacterial dotting.

This spectral fusion allows for precise differentiation between normal and necrotic tissue regions based on wavelength-specific attenuation.

2. Histological Pattern Mapping using Cell-Vein Contrast Ratio (CVCR)

Inspired by microscopic histology, this step involves cell-vein contrast computation using a sliding-window Gabor filter bank. Each window captures micro-patterns of venation, stomatal distribution, and epidermal integrity. The Cell-Vein Contrast Ratio (CVCR) is calculated as:

$$\mathrm{CVCR}(x, y) = \frac{\mu_{\text{cells}}(x, y)}{\mu_{\text{veins}}(x, y) + \epsilon}$$

where μ denotes mean intensity, and ϵ is a small regularization constant to avoid division by zero.

Thresholding this ratio shows zones of vascular collapse, chlorosis, or fungal infiltration without reliance on training data or labeled datasets.

3. Contour-Based Anomaly Isolation

Post CVCR analysis, the method applies adaptive elliptical contouring to isolate irregular lesion margins. The elliptical model adapts to organic growth patterns of necrotic tissue, providing better morphological fit than rectangular bounding techniques. This is followed by:

- Fractal boundary scoring, which calculates the irregularity index of lesion perimeters.

- Texture coherence disruption analysis, measuring deviation from healthy mesophyll patterns.

This helps catch infections early, even when symptoms are just starting to appear.

4. Time-Series Mapping using Phase Drift Correlation (PDC)

To monitor disease progression, the same leaf is scanned periodically and compared using Phase Drift Correlation (PDC) of its spectral histological signature. Changes in phase alignment over time provide a quantitative progression index. The PDC coefficient is defined as:

$$\mathbf{PDC} = \frac{1}{N} \sum_{i=1}^{N} \cos(\phi_i^{(t)} - \phi_i^{(t-1)})$$

where $\phi_i^{(t)}$ represents the spectral phase at time ttt for region iii. A PDC below 0.85 indicates pathological progression.

Steps	Technique Used	Purpose	Output
1. Image Acquisition	High-res RGB or multispectral capture.	Collect detailed leaf image	Raw image
2. Spectral Decomposition	Modified Fourier-Band Fusion	Separate structural components	Fused frequency image
3. Pattern Mapping	CVCR (Cell-Vein Contrast Ratio)	Highlight vein vs. cell regions	CVCR map
4. Anomaly Isolation	Adaptive Elliptical Contouring & Fractal Scoring	Identify disease spots	Lesion boundary map
5. Progress Tracking	Phase Drift Correlation (PDC)	Compare disease over time	Progression coefficient

Table 1: Detail of each stage in the proposed image processing method, showing its function and result.

V. Conclusion

This review gives a far reaching near examination of different man-made brainpower strategies for the location and characterization of sugarcane leaf infections, featuring the qualities and restrictions of techniques, for example, convolutional brain organizations, support vector machines, and group learning. The steps in AI-based leaf disease recognition and classification are image capture, scaling, filtering, segmentation, selection, and feature extraction. Deep learning or machine learning are typically used in identification jobs. This study looked at a number of recent studies that used ML or DL algorithms to find and assess diseases of sugarcane leaves. When compared to lab-conditioned images, ML and DL models perform poorly on real-world picture datasets. DL models beat ML models. Because of the weighty utilization of ML and DL models in order model preparation, many difficulties remain. Most examinations utilized restrictive lab molded picture assortments. It is rare for a model trained on controlled laboratory images to apply to real-world images. Scientists should prepare and test the model with sufficient harmed plant leaf pictures to increment speculation. The model's performance is influenced by the quality and quantity of relevant attributes that are included in it. To reliably extract relevant characteristics from the segmented lesion in the leaf image for use with DL models, employ a suitable segmentation technique. Plant disease identification and classification issues that could affect model efficacy were also the focus of this study. This study will utilize an ongoing framework to recognize and order rural sicknesses and work on's how scientists might interpret execution drivers. The application of AI-based disease detection to precision agriculture, the investigation of cutting-edge AI methods, and the validation of scalable, real-time solutions in a variety of agricultural settings to improve crop health monitoring and management are among the future aims of this research.

References

[1]. V. Bhatnagar, G. Singh, G. Kumar, and R. Gupta, “Internet of Things in Smart Agriculture: Applications and Open Challenges,” *Int. J. Students' Res. Technol. Manag.*, vol. 8, no. 1, pp. 11–17, 2020, doi: https://doi.org/10.18510/ijsrtm.2020.812.

[2]. G. Singh and K. K. Yogi, “A Review on Recognition of Plant Disease using Intelligent Image Retrieval Techniques,” *Asian J. Biol. Life Sci.*, vol. 9, no. 3, pp. 274–285, 2020.

[3]. R. Kaundal, A. S. Kapoor, and G. P. S. Raghava, “Machine learning techniques in disease forecasting: a case study on rice blast prediction,” *BMC Bioinformatics*, vol. 7, pp. 1–16, 2006.

[4]. G. Singh and K. K. Yogi, “Comparison of RSNET model with existing models for potato leaf disease detection,” *Biocatal. Agric. Biotechnol.*, vol. 50, p. 102726, 2023, doi: https://doi.org/10.1016/j.bcab.2023.102726.

[5]. M. Bagga and S. Goyal, “Image-Based Detection and Classification of Plant Diseases using Deep Learning: State-of-the-Art Review,” *J. Adv. Zool.*, vol. 44, no. S-1 SE-Articles, pp. 136–156, Sep. 2023, [Online]. Available: http://jazindia.com/index.php/jaz/article/view/203

[6]. G. Singh and K. K. Yogi, “Usage of Internet of Things Based Devices in Smart Agriculture for Monitoring the field and Pest Control,” in *2022 IEEE Delhi Section Conference (DELCON)*, IEEE, 2022, pp. 1–8.

[7]. A. H. Kulkarni and A. Patil, “Applying image processing technique to detect plant diseases,” *Int. J. Mod. Eng. Res.*, vol. 2, no. 5, pp. 3661–3664, 2012.

[8]. R. Gupta, V. Bhatnagar, G. Kumar, and G. Singh, “Selection of suitable IoT-based End-devices, tools, and technologies for implementing Smart Farming: Issues and Challenges,” *Int. J. Students' Res. Technol. Manag.*, vol. 10, no. 2, pp. 28–35, 2022, doi: 10.18510/ijsrtm.2022.1024.

[9]. G. Singh and K. K. Yogi, “Internet of things-based devices/robots in Agriculture 4.0,” in *Sustainable Communication Networks and Application: Proceedings of ICSCN 2021*, Springer, 2022, pp. 87–102.

[10]. G. Singh, G. Kumar, V. Bhatnagar, A. Srivastava, and K. Jyoti, “Pollution management through internet of things: a substantial solution for

society," *Humanit. Soc. Sci. Rev.*, vol. 7, no. 5, pp. 1231–1237, 2019, doi: 10.18510/hssr.2019.75162.

[11]. M. S. P. Babu and B. S. Rao, "Leaves recognition using back propagation neural network-advice for pest and disease control on crops," *IndiaKisan. Net Expert Advis. Syst.*, pp. 607–626, 2007.

[12]. G. Kumar, G. Singh, V. Bhatanagar, and K. Jyoti, "SCARY DARK SIDE OF ARTIFICIAL INTELLIGENCE: A PERILOUS CONTRIVANCE TO MANKIND," *Humanit. Soc. Sci. Rev.*, vol. 7, no. 5, pp. 1097–1103, 2019, doi: 10.18510/hssr.2019.75146.

[13]. W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," *Bull. Math. Biophys.*, vol. 5, pp. 115–133, 1943.

[14]. J. Heaton, "Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning," *Genet. Program. Evolvable Mach.*, vol. 19, no. 1, pp. 305–307, 2018, doi: 10.1007/s10710-017-9314-z.

[15]. M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant disease detection and classification by deep learning," *Plants*, vol. 8, no. 11, p. 468, 2019.

[16]. S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Front. Plant Sci.*, vol. 7, p. 1419, 2016.

[17]. A. Narmilan, F. Gonzalez, A. S. Salgadoe, and K. Powell, "Detection of White Leaf Disease in Sugarcane Using Machine Learning Techniques over UAV Multispectral Images," *Drones*, vol. 6, no. 9. 2022. doi: 10.3390/drones6090230.

[18]. E. K. Ratnasari, M. Mentari, R. K. Dewi, and R. V. H. Ginardi, "Sugarcane leaf disease detection and severity estimation based on segmented spots image," in *Proceedings of International Conference on Information, Communication Technology and System (ICTS) 2014*, IEEE, 2014, pp. 93–98.

[19]. D. A. Padilla, G. V. Magwili, A. L. A. Marohom, C. M. G. Co, J. C. C. Gaño, and J. M. U. Tuazon, "Portable Yellow Spot Disease Identifier on Sugarcane Leaf via Image Processing Using Support Vector Machine," *2019 5th Int. Conf. Control. Autom. Robot. ICCAR 2019*, pp. 901–905, 2019, doi: 10.1109/ICCAR.2019.8813495.

[20]. A. Kumar, "Detection of Sugarcane Disease and Classification using Image Processing," *Int. J. Res. Appl. Sci. Eng. Technol.*, vol. 7, no. 5, pp. 2023–2030, 2019, doi: 10.22214/ijraset.2019.5338.

[21]. K. Renugambal and B. Senthilraja, "Application of image processing techniques in plant disease recognition," *Int. J. Eng. Res. Technol.*, vol. 4, no. 3, pp. 919–923, 2015.

[22]. D. J. S. Umapathy Eaganathan, V. Lackose, and F. J. Benjamin, "Identification of sugarcane leaf scorch disease using K-means clustering segmentation and KNN based classification," *Int. J. Adv. Comput. Sci. Technol.*, vol. 3, no. 12, pp. 11–16, 2014.

[23]. K. Thilagavathi, K. Kavitha, R. D. Praba, S. V Arina, and R. C. Sahana, "Detection of diseases in sugarcane using image processing techniques," *Biosci. Biotechnol. Res. Commun. Spec. Issue*, no. 11, pp. 109–115, 2020.

[24]. U. Eaganathan, J. Sophia, V. Luckose, and F. J. Benjamin, "Identification of Sugarcane Leaf Scorch Diseases using K-means Clustering Segmentation and K-NN based Classification," vol. 3, no. 12, pp. 11–16, 2014.

[25]. S. A. Upadhye, M. R. Dhanvijay, and S. M. Patil, "Sugarcane Disease Detection Using CNN-Deep Learning Method: An Indian Perspective," *Univers. J. Agric. Res.*, vol. 11, no. 1, pp. 80–97, 2023, doi: 10.13189/ujar.2023.110108.

[26]. U. Vignesh and B. S. Chokkalingam, "EnC-SVMWEL: Ensemble Approach using CNN and SVM Weighted Average Ensemble Learning for Sugarcane Leaf Disease Detection," in *2023 International Conference on Sustainable Computing and Data*

Communication Systems (ICSCDS), 2023, pp. 1663–1668. doi: 10.1109/ICSCDS56580.2023.10104818.

[27]. X. Li, X. Li, S. Zhang, G. Zhang, M. Zhang, and H. Shang, "SLViT: Shuffle-convolution-based lightweight Vision transformer for effective diagnosis of sugarcane leaf diseases," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 35, no. 6, p. 101401, 2023, doi: https://doi.org/10.1016/j.jksuci.2022.09.013.

[28]. T. Tamilvizhi, R. Surendran, K. Anbazhagan, and K. Rajkumar, "Quantum Behaved Particle Swarm Optimization-Based Deep Transfer Learning Model for Sugarcane Leaf Disease Detection and Classification," *Math. Probl. Eng.*, vol. 2022, p. 3452413, 2022, doi: 10.1155/2022/3452413.

[29]. H. S. Malik *et al.*, "Disease Recognition in Sugarcane Crop Using Deep Learning," *Adv. Intell. Syst. Comput.*, vol. 1133, no. September, pp. 189–206, 2021, doi: 10.1007/978-981-15-3514-7_17.

[30]. R. Manavalan, "Efficient Detection of Sugarcane Diseases through Intelligent Approaches: A Review," *Asian J. Res. Rev. Agric.*, vol. 3, no. 1 SE-Mini Review Papers, pp. 174–184, Aug. 2021, [Online]. Available: https://www.globalpresshub.com/index.php/AJRRA/article/view/1237

[31]. S. D. Daphal and S. M. Koli, "Transfer Learning approach to Sugarcane Foliar disease Classification with state-of-the-art Sugarcane Database," in *2021 International Conference on Computational Intelligence and Computing Applications (ICCICA)*, 2021, pp. 1–4. doi: 10.1109/ICCICA52458.2021.9697312.

[32]. S. Srivastava, P. Kumar, N. Mohd, A. Singh, and F. S. Gill, "A Novel Deep Learning Framework Approach for Sugarcane Disease Detection," *SN Comput. Sci.*, vol. 1, no. 2, p. 87, 2020, doi: 10.1007/s42979-020-0094-9.

[33]. S. Srivastava, P. Kumar, N. Mohd, A. Singh, and F. S. Gill, "A Novel Deep Learning Framework Approach for Sugarcane Disease Detection," *SN Comput. Sci.*, vol. 1, no. 2, p. 87, 2020, doi: 10.1007/s42979-020-0094-9.

[34]. D. Bao, J. Zhou, S. A. Bhuiyan, A. Zia, R. Ford, and Y. Gao, "Early Detection of Sugarcane Smut Disease in Hyperspectral Images," in *2021 36th International Conference on Image and Vision Computing New Zealand (IVCNZ)*, IEEE, 2021, pp. 1–6.Muhammad Farhan, Khujamshukurov, N. A., Fatima, Z., Ahmad, T., Zaid, M., Anton, K., ... (2025). The status of smart agriculture: A method to enhancing management. Smart Systems, 2025, 53–68.

[35]. Farhan, M., Khujamshukurov, N. A., Fatima, Z., Ahmad, T., Zaid, M., Anton, K., ... (2025). The status of smart agriculture: A method to enhancing management. *Smart Systems*, *2025*, 53–68.

[36]. Farhan, M., Taha, M. M., Yusuf, Y., Sundi, S. A., & Zakaria, N. H. (2024). Environmental assessment on fabrication of bio-composite filament fused deposition modeling through life cycle analysis. *Pertanika Journal of Science & Technology*, *32*.

[37]. Khan, S., Akhtar, J., Farhan, M., Khujamshukurov, N. A., Khan, M. I., Ahmad, M., ... (2024). Quality assurance framework for smart drug delivery systems in pharmaceutical industries and its applications. *Smart Systems*, *2024*, 198–211.

[38]. Farhan, M., Khursheed, S., Alam, M. A., Azeem, M., & Muaz, M. (2024). Smart ergonomic design of VDT workstation. *Smart Systems: Methodological Approaches and Applications*, *2024*, 185.

[39]. Fatima, Z., Farhan, M., Mohiuddin, G., Zaid, M., Khan, M. U., & Muaz, M. (2024). Methodological approaches for smart agriculture and its applications. *Smart Systems*, *2024*, 69–87.

[40]. Huzefa, S., Nazir, A., Sufiyan, M., Syed, H. A., Zoha, F., Mugish, M., & Farhan, M. (2024). Designing an effective real-time fraud detection system with

machine learning techniques. In *International Conference on Advances in Science, Engineering and Technology (ICASET-2024)*.

[41]. Fatima, Z., Farhan, M., Mohiuddin, G., Zaid, M., & Sohail, S. S. (2024). Intelligent diagnostic harmony automation: CNN-RNN approach for the early detection of pancreatic disease. In *International Conference on Mechanical Engineering Ideas, Innovations (2024)*.

[42]. Zaid, M., Farhan, M., & Tabrej, K. (2024). A design approach to reduce torsional vibrations in shaft of WECS with the help of non-linear observer. In *International Conference on Mechanical Engineering Ideas, Innovations (2024)*.

[43]. Asif, M., Akhtar, J., Farhan, M., Badruddeen, Khan, M. I., & Ahmad, M. (2022). Development and evaluation of levofloxacin pro-liposomes by micronized sucrose method: A sustainable gastronomy approach. In *INDO-UZBEK MEET & International Conference on Trends & Innovations in Food (2022)*.

[44]. Farhan, M., Imran, J., Akhtar, J., Azeem, M., & Sumita. (2022). Recent developments in single-use plastic packaging sustainable alternatives in food industry: An affordable way to go economic green. In *INDO-UZBEK MEET & International Conference on Trends & Innovations in Food (2022)*.

[45]. Farhan, M., Sadique, M., & Khan, M. S. (2022). Design & development of small portable table by sugar palm fibre reinforced unsaturated polyester composites. In *National Conference on Synthesis, Properties and Applications of Materials (NCFM-2022)*.

[46]. Farhan, M., Azeem, M., Kaladgi, A. R., Afzal, A., & Chandrashekar. (2022). A survey of the most recent developments in tachometer speed measurement technology. In *Second International Conference on Materials and Technologies (MaterialTECH-2022)*.

[47]. Jamil, A., & Farhan, M. (2022). Advanced potential hybrid biocomposites – An affordable way to go green. In *Research & Industrial Conclave Integration 2022*, IIT Guwahati.

[48]. Farhan, M., Mastura, M. T., Ansari, S. P., Muaz, M., & Azeem, M. (2022). Advanced potential hybrid biocomposites in aerospace applications: A comprehensive review. In *Advanced Composites in Aerospace Engineering Applications* (pp. 127–148).

[49]. Farhan, M., & Ansari, M. S. (2019). Engineering efficacy of sugar palm tree fibre (*Arenga pinnata*) grown in various regions of India: A review. In *2nd International Conference on Chemistry, Industry and Environment (ICCIE-2019)*.

[50]. Farhan, M., & Mohd. Anas, M. A. (2018). Rolling barriers: Emerging concept to reduce road accidents: An Indian perspective. *Materials Science and Engineering*, *404*, 012045.

[51]. Farhan, M., & Alam, K. (2018). A review of the advancements in tachometer for speed measurement. In *IEEE International Conference on Computational and Characterization Techniques in Engineering & Sciences (CCTES 2018)*.

[52]. Khujamshukurov, N. A., Farhan, M., Eshkobilov, S. A., Kuchkarova, D. X., ... (n.d.). Impact of biohumus on soil agrochemical characteristics, fertility, and plant performance under greenhouse conditions. *Smart Systems*, *n.d.*, 145–184.

[53]. Kumar, P., Verma, A., Fatima, U., Siddiqui, N., Khan, M. A., Khan, N., Pandey, R. K., Razdan, D., Ranjan, R., Abbas, S. H., & Farhan, M. (2025). Sustainable healthcare through IoT and pervasive computing: A reinforcement learning approach. *Journal of Neonatal Surgery*, *14*(10s), 429–436.

[54]. Khan, F., Bharti, P. K., Heshamuddin, M., Farhan, M., Farade, R. A., & Khalique Ahmad, A. A. (2025). Analysis of ethical and social implications of artificial intelligence (AI). In *2025 International Conference on Cognitive Computing in Engineering, Communications, Sciences and Biomedical Health Informatics (IC3ECSBHI)* (pp. 1058–1061). https://doi.org/10.1109/IC3ECSBHI63591

.2025.10991260

[55]. Abu Bakr, M., Farhan, M., Khursheed, S., Haq, N., & Hasnain, S. M. M. (2025). Sustainable self-compacting recycled aggregate concrete incorporating industrial byproducts and agricultural waste: Rheological, strength, and durability properties. *ACS Omega*. https://doi.org/10.1021/acsomega.4c10374

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