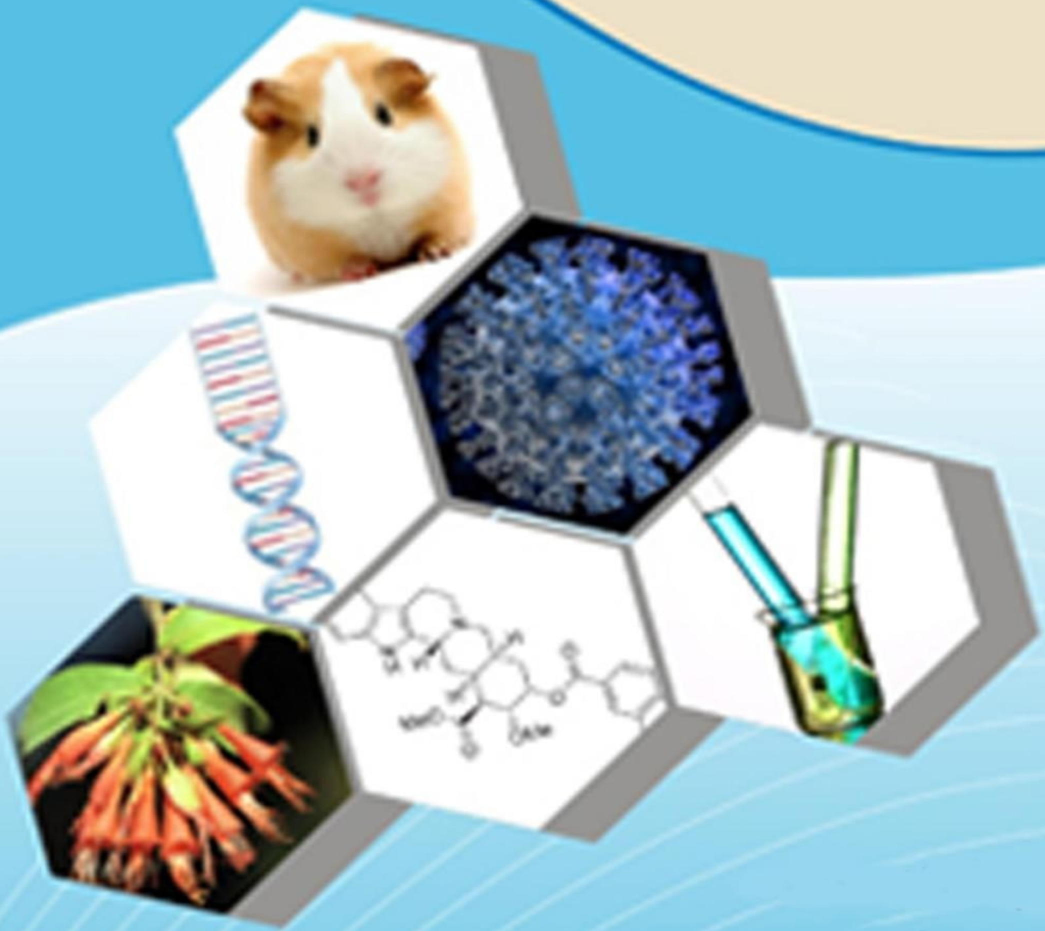
ISSN : 2347-2251

Indo-American Journal of Pharma and Bio Sciences



iajpb.editor@gmail.com
editor@iajpb.com

www.iajpb.com

ISSN 2347-2251 www.iajpb.com
Vol. 22, Issue 4, 2024
Indo-American Journal of Pharma and Bio Sciences

A NOVEL DEEP LEARNING FRAMEWORK FOR PLANT DISEASE DETECTION USING EFFICIENTNET MODEL

[1]**Rahul Jadon**
Cargurus, USA
rahul.jadon0@gmail.com

[2]**Kannan Srinivasan**
Senior Software Engineer
Saiana Technologies Inc, New Jersey, USA
kannan.srini3108@gmail.com

[3]**Guman Singh Chauhan**
John Tesla Inc,
Texas, USA
gumanc38@gmail.com

[4]**Rajababu Budda**
IBM,San Francisco, California, USA
RajBudda55@gmail.com

[5]**Venkata Surya Teja Gollapalli**
Senior System Engineer,
Centene Management Company LLC,
Missouri, USA,
venkatasuryagollapalli@gmail.com

[6]**R. Mekala**
Sri Ranganathar Institute of Engineering and Technology
Coimbatore, India.
mail2dr.mekala@gmail.com

ABSTRACT

Global agricultural output is seriously threatened by plant diseases, which must be identified quickly and accurately to minimize crop loss and improve farming methods. Outdated methods of disease identification, relying on expert knowledge and manual inspection, are time-consuming and prone to errors, making it challenging to address large-scale agricultural monitoring. To address these challenges, this work presents a deep learning (DL)-based system for accurate plant disease detection using the EfficientNet architecture. The system begins with data collection, where a plant disease dataset of healthy and diseased plant leaves is gathered. Data preprocessing follows, including image resizing for uniformity and data augmentation to increase the dataset size and diversity. Once the data is pre-processed, feature extraction is performed using Histogram of Oriented Gradients to capture key texture and edge features from the images. The EfficientNet model is then selected and trained on the extracted features for plant disease classification. The results show that the training accuracy reached 0.988, and the training loss dropped to 0.033, with similar performance observed for validation, where accuracy reached 0.988 and loss also converged to 0.033, indicating strong model performance. This work proposes a computationally efficient, accurate DL-based framework for plant disease classification, demonstrating both high accuracy and generalization capability for applications in agriculture.

Keywords: Plant Disease Detection, Image Classification, EfficientNet, Deep Learning, Histogram of Oriented Gradients, Feature Extraction.

1 INTRODUCTION

Plant diseases are counted as general drawbacks to the agricultural productivity of all places on the planet and are one of the many threats to food security [1]. Early detection and accurate classification of plant diseases can prevent the loss of crops, the use of pesticides and aid in generally farm management [2]. The conventional methods of identifying plant diseases depended on manual checks, which are tedious, subjective, and therefore prone to errors [3]. This has increased a lot of interest in machine learning (ML) and computer vision in making automated detection of plant diseases [4]. The idea of using EfficientNet and other similar models for classifying plant diseases would mean that such a method could be accurate and scale up to real agricultural applications [5]. Thus, this framework promises to deliver an efficient solution for plant disease prediction with high accuracy using modern deep learning (DL) systems [6].

Various methods have been proposed for plant disease detection, ranging from outdated image processing methods to modern ML paradigms [7]. Earlier procedures focused mainly on basic feature extraction, such as colors, texture and shape to classify diseases, using methods like support vector machine or k-nearest neighbor [8]. The outdated methods attempted to use a deep learning model like convolutional neural networks, which were very successful in image classification tasks [9]. The prominent approaches are based on ResNet, VGGNet and InceptionNet for plant disease classification [10]. The major challenges faced by these methodologies comprise high computational costs, overfitting due to lack of data, and limited generalized ability across different plant species [11]. To date, while CNNs perform well when datasets are large, they have been shown to either underperform or become computationally inefficient when given small-sized datasets or datasets with great diversity in the class of plant diseases [12].

The proposed framework resolves the limitations of current techniques by integrating EfficientNet, known for attaining efficacy and scale in deep learning [13]. Developed through advanced means, EfficientNet performs better than other techniques while using lesser computations in the achievement. This allows EfficientNet to perform well in plant disease detection [14]. It will enable good processing of large and small datasets; it will help in overfitting problems in generalization [15]. The conjectural novelty of this system is that it can turn out EfficientNet's very lightweight but powerful designs for plant disease classification into swift and accurate predictions as opposed to the fast-deployed computational models of today [16]. In fact, this framework takes a big step forward in automated plant disease detection. The paper is organized as follows: Section 2 analyses related works, discussing previous approaches and their limitations. Section 3 presents the methodology [17]. Section 4 provides the results and performance analysis. Lastly, Section 5 concludes the paper.

Plant diseases are a significant challenge to global agriculture, posing a direct threat to food security by reducing crop yields. Early and accurate detection of these diseases is essential for preventing crop loss, reducing pesticide usage, and enhancing overall farm management [18]. Traditional methods of plant disease detection relied heavily on manual inspection, which is not only time-consuming but also prone to human error. As a result, there has been a growing interest in applying machine learning (ML) and computer vision techniques to automate the process of plant disease detection [19]. The use of modern deep learning (DL) systems, such as EfficientNet, offers the promise of accurate, scalable, and efficient solutions for classifying plant diseases, making them suitable for real-world agricultural applications. Historically, plant disease detection methods relied on basic image processing techniques, such as feature extraction based on color, texture, and shape. These approaches often utilized machine learning models like Support Vector Machines (SVMs) or k-Nearest Neighbors (k-NN) to classify diseases. While these methods were effective to an extent, they faced significant limitations, especially when dealing with large and complex image datasets [20]. The rise of Convolutional Neural Networks (CNNs) marked a significant advancement in this field due to their strong performance in image classification tasks. However, CNN-based models such as ResNet, VGGNet, and InceptionNet faced challenges, including high computational demands, overfitting when trained on limited data, and poor generalization across diverse plant species and disease types.

2 LITERATURE SURVEY

Over the years, several studies have focused on improving prediction accuracy for various ailments using hybrid models combined with real-time monitoring systems [21]. A notable approach involved the development of systems integrating scalable cloud architectures with IoT sensors to collect data, optimize features, and classify diseases [22]. These systems have shown promise in various applications, including chronic disease monitoring and remote healthcare management, leveraging wearable IoT devices and cloud capabilities to enhance the effectiveness of healthcare delivery [23]. Some studies also utilized graph theory and multi-omics integration to study disease dynamics, such as lung cancer, providing valuable insights for better patient outcomes through predictive modeling [24]. Additionally, hybrid models combining stochastic fuzzy systems with advanced machine learning techniques like BiLSTM have proven useful in improving prediction accuracy for diseases like chronic kidney disease by addressing the inherent uncertainty in medical data [25].

Advancements in AI and machine learning have also led to the development of dynamic models aimed at improving cloud resource management, security, and efficiency, especially in the context of healthcare [26]. Deep learning and reinforcement learning techniques have been employed to optimize clinical decision-making and enhance predictive accuracy, ultimately leading to better patient treatment strategies [27]. Some research has focused on leveraging machine learning models interfaced with cloud-based Electronic Medical Records (EMR) analytics for predicting pediatric readmissions with greater precision, while others have proposed cloud-based systems for forecasting healthcare risks by utilizing IoT devices and decision trees [28]. These hybrid approaches contribute to surgical decision-making and patient safety by providing real-time, data-driven insights for healthcare professionals [29].

Furthermore, the use of AI-driven models for disease detection has extended to various other domains, including fall detection, chronic disease management, and even cybersecurity [30]. Models incorporating supervised learning algorithms like Random Forests, Support Vector Machines, and Neural Networks have shown effectiveness in managing chronic diseases and providing predictive healthcare in geriatric settings [31]. Hybrid models combining Convolutional Neural Networks (CNNs) with other optimization techniques like Differential Evolutionary-Extreme Learning Machines (DEELM) have improved disease detection accuracy and speed [32]. Additionally, AI-based systems have been proposed to enhance cybersecurity, leveraging hybrid models like CNNs, Transformers, and Long Short-Term Memory (LSTM) networks for high-accuracy detection of side-channel attacks on embedded systems [33]. In the realm of healthcare, efficient and scalable architectures like EfficientNet are being explored to increase accuracy in disease detection, offering a promising solution for real-time, automated healthcare predictions [34].

In addition to the advancements in disease prediction and healthcare monitoring, there has been significant progress in utilizing machine learning models to enhance diagnostic precision and system scalability across various industries [35]. For instance, next-generation healthcare systems are being designed with lightweight architectures, such as capsule networks and CNNs, combined with decentralized data security protocols like blockchain [36]. These systems aim to improve diagnostic accuracy while ensuring the integrity and privacy of sensitive health data. Similarly, machine learning-based models, such as Decision Trees and K-Nearest Neighbors, are being employed in cybersecurity to detect anomalies in IoT networks, helping to secure connected devices [37]. Further developments in anomaly detection, such as Transformer-based models for financial fraud detection, have also demonstrated the potential of machine learning in identifying irregular patterns in transaction sequences [38]. By enhancing the precision, scalability, and efficiency of these models, researchers are pushing the boundaries of automated detection across diverse sectors, with promising implications for future applications in both healthcare and cybersecurity [39]. Recent advancements in machine learning have significantly impacted multiple industries, improving both operational efficiency and decision-making accuracy [40]. In healthcare, the integration of AI models with wearable devices and cloud-based systems is transforming patient monitoring and disease management [41]. These systems can collect real-time data, analyze it using deep learning algorithms, and provide actionable insights, enabling early detection of health issues and personalized treatment plans [42]. Additionally, machine learning algorithms are being applied in medical imaging, where they aid in detecting abnormalities, such as tumours, with higher precision than traditional methods. These advancements in diagnostic accuracy are particularly beneficial in resource-constrained environments, where timely intervention can make a significant difference [43].

2.1 Problem Statement

The existing work is quite good, but there are still challenges to be resolved, namely, high computation costs, insufficient data and feature extraction complexity [44]. Computation cost is a critical issue, wherein classical deep learning models need huge processing resources that can render these models unable to work in real-time onto devices with limited resources [45]. Data insufficiency is also an issue, in which many of the datasets dealing with plant diseases are either small or unbalanced [46]. As a result, models may not be able to generalize to new or unseen data. Also, feature extraction in classical methods is complex, requiring manual intervention; hence, it cannot capture the complex patterns in plant disease images [47]. This work seeks to address these challenges using the EfficientNet architecture to minimize computation costs, data augmentation techniques to remedy data insufficiency and the use of DL for automatic feature extraction to ease the process [48]. Additionally, EfficientNet's lightweight design enables it to achieve high accuracy with fewer resources, making it more suitable for deployment on devices with limited computational capacity [49]. Data augmentation techniques, such as rotation, scaling, and flipping, help expand the dataset and address issues related to data imbalance, improving the model’s ability to generalize to new plant diseases [50]. By automating the feature extraction process, the model can efficiently detect intricate patterns in plant disease images without the need for manual intervention, further enhancing its scalability and reliability in real-world applications [51].

3 METHODOLOGIES

Plant Disease Prediction Workflow data collection process starts with formation of a dataset that consists of images for healthy and diseased leaves of a specific crop. The next stage is data preprocessing which comprises resizing of images on uniform scale and augmented data to prevent overfitting. HOG is a technique of extracting feature whereby images are described in terms of texture and edge. Later, the extracted features were used to train the EfficientNet deep network model for efficient and effective performance on image classification problems. Then, it shows that the model assessment will be represented with various metrics like accuracy, recall, precision and F1-score. The overall process of predicting plant diseases has been shown in Figure 1.

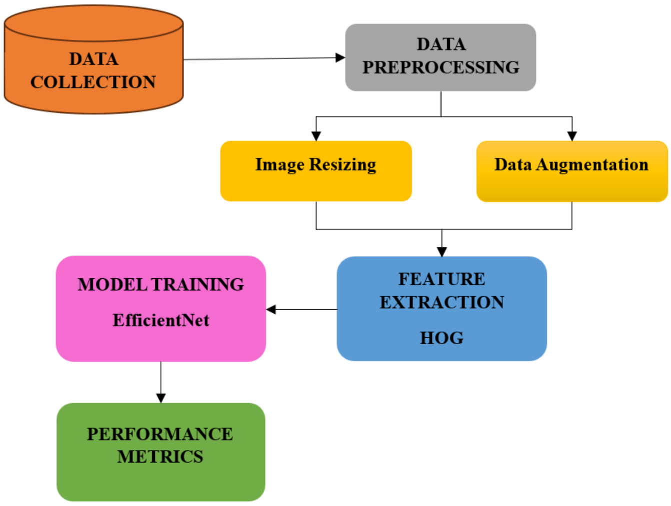


Figure 1: Workflow of Plant Disease Classification Using EfficientNet

3.1 Data Collection

Data collection is about compiling a full plant disease database that has healthy as well as diseased crop leaves, typically described with a multitude of photographs. The database has RGB images classified into different classes that categorize the images according to the diseases, and pretty much every plant species has its separate set of images. Images will be entrenched into public agricultural datasets in addition to those collected by alliance with agricultural institutions. The collected data are under different conditions of light, angle, and environment so as to make them robust. The collected dataset is subjected to separating it into training, validation, and testing subsets for performance evaluation. Further, various augmentation techniques are applied to increase data and avoid overfitting.

3.2 Data Preprocessing

Data preprocessing procedures list some vital procedures to prime the dataset for training using a DL model. The first step is image enlargement, in which the collected images are being enlarged to conform to a standard dimension. This implies that all determined images are consistent in their dimension that is important as input into the cell-type neural networks. The other added advantage to the procedure is that resizing may help in reducing computational expenses and hence would ensure the model to efficiently process the data without going for memory overload. Lastly, since resizing may help in standardizing the features within the image, the model learns relevant patterns from images of different sizes more easily.

In the second step, data augmentation, some procedures are done for artificially expanding the dataset. Some of the changes appearing in the random transformations include rotation, zooming, flipping and color variation of the original images. Data augmentation is intended to introduce variance into the training set, thereby increasing the model’s generalization to new, unseen data. Data augmentation also provides less chance of overfitting by enriching the dataset so that the model doesn't memorize specific patterns in the training data but instead learns more generalizable features that can be applied to different plant disease images.

3.3 Feature Extraction

After the preprocessing of data, feature extraction is carried out using HOG, which assists in the extraction of important texture and shape features of the images. The HOG works in such a way that it divides the image into small cells and finds the gradient direction for each of the cells, by which the edges and contours of plant leaves can be distinguished. These gradients are accumulated to make a histogram that can capture the dominant directions of edges within a region of the whole image. The model thus concentrates on important patterns, such as of leaf veins, spots, and lesions, associated with certain diseases. This will, therefore, extract features and ultimately simplify the image data so that it will be easy for the DL model to process and classify the plant diseases effectively.

3.4 Model Training

Once the features have been extracted using HOG, model selection for a plant disease classification is very crucial. The model picked in this instance is EfficientNet since the architecture balances a performance level with a low computational cost more efficiently than most others. EfficientNet is thus superior in working with this type of features obtained from plant leaf images, as it captures more sophisticated patterns with generally fewer parameters than conventional CNNs. The model now drills the values of the data set that has been preprocessed and fed with the extracted features using suitable optimizers like Adam or SGD to minimize the loss function. By this stage, the model classifies images into categories of diseases by updating weighed according to prediction errors in respect to performance measures being considered-telling us if the model performance is good or not such accuracies, precision and recall. Regularly validating the model guarantees that some overfitting is avoided while also assuring competence of detection on the unseen data.

In the context of model selection and training, let's mathematically represent the process for the EfficientNet model, considering the features extracted from the images.

The process begins by selecting EfficientNet based on its ability to scale efficiently with the dataset and minimize computational resources. EfficientNet uses a compound scaling method to scale up the width, depth, and resolution of the network efficiently. The scaling strategy is defined as equation (1),

$$Scale\ Factor\ = \alpha^{depth}, \beta^{width}, \gamma^{resolution} \tag{1}$$

Where, α, β, and γ are hyperparameters that control the scaling of the width, depth, and resolution of the model, respectively. These parameters are optimized to balance model accuracy and efficiency.

The training process involves minimizing the loss function using optimization algorithms like Adam or Stochastic Gradient Descent. The loss function L can be represented as equation (2),

$$L = \frac{1}{N} \sum_{i=1}^{N} \quad L_{loss} (y_i, y\hat{}_i) \tag{2}$$

Where, N signifies the total number of training samples. y_i shows the true label for the i-th sample. $y\hat{}_i$ denotes the predicted label for the i-th sample. L_{loss} is the chosen loss function. In the case of EfficientNet, the model adjusts its weights θ during training to minimize the loss function.

The weight update rule for Adam optimizer is given by equation (3),

$$\theta_{t+1} = \theta_t - \eta \cdot m\hat{}_t / (v\hat{}_t + \epsilon) \tag{3}$$

Where, η denotes the learning rate. $m\hat{}_t$ symbolizes the bias-corrected first moment estimate. $v\hat{}_t$ is the bias-corrected second moment estimate. ϵ is a small constant to prevent division by zero. This mathematical framework provides a structured approach for model selection, training, and evaluation of the EfficientNet architecture for plant disease classification.

4 *RESULTS*

The results for the plant disease classification model manifest its high performance and efficiency. The training and validation metrics have shown progressive improvement with already achieved high accuracy and less loss through the epochs. Besides, the ROC curve analysis will prove how well the model can differentiate between plant diseases with a high value on AUC.

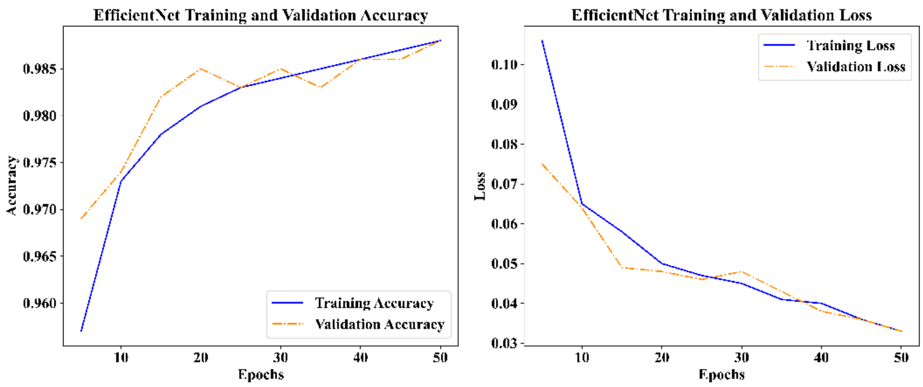


Figure 2: EfficientNet Training and Validation Accuracy and Loss over Epochs

The Figure 2 is depicted, which presents the accuracy during training and validation (left) and loss in training and validation (right) across ten epochs for the EfficientNet model. The value of training accuracy increased to 0.988, while the training loss decreased to 0.033, which indicates a very good improvement during the training phase. For validation accuracy, it was also 0.988, and for validation loss, it is 0.033. Such results suggest that the model is performing well and that accuracy and loss are approaching their limit values, with an almost imperceptible overfitting, resulting in a small difference between training and validation curves.

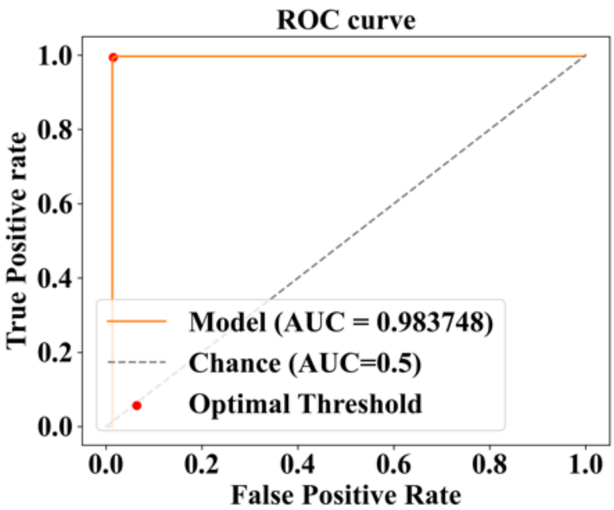


Figure 3: ROC Curve

The ROC curve corresponding to the model for plant diseases classification with an AUC of 0.9837 is shown in Figure 3; this indicates that the model performed excellently. The chance line, which represents a random classifier, has an AUC of 0.5, thus shedding more light upon the strong performance of the proposed model over random guessing. The point on the curve corresponding to the optimal threshold shows the point at which the best trade-off between the false positive rate and true positive rate is reached by the model. Thus, it validates that the model can well segregate plant diseased categories with high predictive validity.

5 CONCLUSIONS

The study aimed toward the successful development of a fast and accurate plant disease classification system using DL. The EfficientNet has performed exceptionally well, reaching a training and validation accuracy of 0.988 with a loss of 0.033, and all converge to the model very strongly. The ROC curve

AUC value of 0.9837 confirms the model's efficient discrimination between diseased and healthy plant leaves. The efficiency of the system, both in resource use and accuracy, thus recommends its use in real-time applications in agriculture. High prediction accuracy with less chance of overfitting is thus generated through feature extraction methods like HOG and the scalable architecture of EfficientNet. Future work will delve into linking the prediction model of disease control with the automated decision-making algorithm to optimize pesticide application and improve resource use.

REFERENCES

[1] Chug, A., Bhatia, A., Singh, A. P., & Singh, D. (2023). A novel framework for image-based plant disease detection using hybrid deep learning approach. Soft Computing, 27(18), 13613-13638.

[2] Gollavilli, V. S. B. H., & Arulkumaran, G. (2019). Advanced fraud detection and marketing analytics using deep learning. Journal of Science & Technology, 4(3).

[3] Mahum, R., Munir, H., Mughal, Z. U. N., Awais, M., Sher Khan, F., Saqlain, M., ... & Tlili, I. (2023). A novel framework for potato leaf disease detection using an efficient deep learning model. Human and Ecological Risk Assessment: An International Journal, 29(2), 303-326.

[4] Gollapalli, V. S. T., & Padmavathy, R. (2019). AI-driven intrusion detection system using autoencoders and LSTM for enhanced network security. Journal of Science & Technology, 4(4).

[5] Podder, P., Das, S. R., Mondal, M. R. H., Bharati, S., Maliha, A., Hasan, M. J., & Piltan, F. (2023). Lddnet: a deep learning framework for the diagnosis of infectious lung diseases. Sensors, 23(1), 480.

[6] Mandala, R. R., & Hemnath, R. (2019). Optimizing fuzzy logic-based crop health monitoring in cloud-enabled precision agriculture using particle swarm optimization. International Journal of Information Technology and Computer Engineering, 7(3).

[7] Ali, S. N., Shuvo, S. B., Al-Manzo, M. I. S., Hasan, A., & Hasan, T. (2023). An end-to-end deep learning framework for real-time denoising of heart sounds for cardiac disease detection in unseen noise. IEEE Access, 11, 87887-87901.

[8] Garikipati, V., & Pushpakumar, R. (2019). Integrating cloud computing with predictive AI models for efficient fault detection in robotic software. International Journal of Engineering Science and Advanced Technology (IJESAT), 19(5).

[9] Jasmine Pemeena Priyadarsini, M., Kotecha, K., Rajini, G. K., Hariharan, K., Utkarsh Raj, K., Bhargav Ram, K., ... & Pandya, S. (2023). Lung diseases detection using various deep learning algorithms. Journal of healthcare engineering, 2023(1), 3563696.

[10] Ayyadurai, R., & Kurunthachalam, A. (2019). Enhancing financial security and fraud detection using AI. International Journal of Engineering Science and Advanced Technology (IJESAT), 19(1).

[11] Arun, R. A., & Umamaheswari, S. (2023). Effective multi-crop disease detection using pruned complete concatenated deep learning model. Expert Systems with Applications, 213, 118905.

[12] Basani, D. K. R., & Bharathidasan, S. (2019). IoT-driven adaptive soil monitoring using hybrid hexagonal grid mapping and kriging-based terrain estimation for smart farming robots. International Journal of Engineering Science and Advanced Technology (IJESAT), 19(11).

[13] Choudhary, A., Ahlawat, S., Urooj, S., Pathak, N., Lay-Ekuakille, A., & Sharma, N. (2023, January). A deep learning-based framework for retinal disease classification. In Healthcare (Vol. 11, No. 2, p. 212). MDPI.

[14] Kodadi, S., & Purandhar, N. (2019). Optimizing secure multi-party computation for healthcare data protection in the cloud using hybrid garbled circuits. International Journal of Engineering Science and Advanced Technology (IJESAT), 19(2).

[15] Arshad, F., Mateen, M., Hayat, S., Wardah, M., Al-Huda, Z., Gu, Y. H., & Al-antari, M. A. (2023). PLDPNet: End-to-end hybrid deep learning framework for potato leaf disease prediction. Alexandria Engineering Journal, 78, 406-418.

[16] Devarajan, M. V., & Pushpakumar, R. (2019). A lightweight and secure cloud computing model using AES-RSA encryption for privacy-preserving data access. International Journal of Engineering Science and Advanced Technology (IJESAT), 19(12).

[17] Khan, A. M., Akram, M. U., Nazir, S., Hassan, T., Khawaja, S. G., & Fatima, T. (2023). Multi-head deep learning framework for pulmonary disease detection and severity scoring with modified progressive learning. Biomedical Signal Processing and Control, 85, 104855.

[18] Allur, N. S., & Thanjaivadivel, M. (2019). Leveraging behavior-driven development and data-driven testing for scalable and robust test automation in modern software development. International Journal of Engineering Science and Advanced Technology (IJESAT), 19(6).

[19] Sharma, R., Kukreja, V., & Gupta, R. (2023, May). Enhancing wheat crop resilience: An efficient deep learning framework for the detection and classification of rust disease. In 2023 4th International Conference for Emerging Technology (INCET) (pp. 1-5). IEEE.

[20] Bobba, J., & Kurunthachalam, A. (2020). Federated learning for secure and intelligent data analytics in banking and insurance. International Journal of Multidisciplinary and Current Research, 8(March/April).

[21] Saif, D., Sarhan, A. M., & Elshennawy, N. M. (2023). Deep-kidney: an effective deep learning framework for chronic kidney disease prediction. Health Information Science and Systems, 12(1), 3.

[22] Gollavilli, V. S. B. H., & Pushpakumar, R. (2020). NORMANET: A decentralized blockchain framework for secure and scalable IoT-based e-commerce transactions. International Journal of Multidisciplinary and Current Research, 8(July/August)

[23] Xu, L., Cao, B., Zhao, F., Ning, S., Xu, P., Zhang, W., & Hou, X. (2023). Wheat leaf disease identification based on deep learning algorithms. Physiological and Molecular Plant Pathology, 123, 101940.

[24] Grandhi, S. H., & Arulkumaran, G. (2020). AI solutions for SDN routing optimization using graph neural networks in traffic engineering. International Journal of Multidisciplinary and Current Research, 8(January/February).

[25] Jha, P., Dembla, D., & Dubey, W. (2023, February). Comparative Analysis of Crop Diseases Detection Using Machine Learning Algorithm. In 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS) (pp. 569-574). IEEE.

[26] Nippatla, R. P., & Palanisamy, P. (2020). Optimized cloud architecture for scalable and secure accounting systems in the digital era. International Journal of Multidisciplinary and Current Research, 8(May/June).

[27] Abd El-Fattah, I., Ali, A. M., El-Shafai, W., Taha, T. E., & Abd El-Samie, F. E. (2023). Deep-learning-based super-resolution and classification framework for skin disease detection applications. Optical and Quantum Electronics, 55(5), 427.

[28] Kushala, K., & Thanjaivadivel, M. (2020). Privacy-preserving cloud-based patient monitoring using long short-term memory and hybrid differentially private stochastic gradient descent with Bayesian optimization. International Journal in Physical and Applied Sciences, 7(8).

[29] Chandralekha, E., Vinodhini, S., Kandasamy, V., Rama, P., Ravikumar, S., & Saravanan, T. R. (2023, December). An Extensive Machine Learning Framework Employing Ensemble Classifiers for Heart Disease Detection. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 973-978). IEEE.

[30] Garikipati, V., & Bharathidasan, S. (2020). Enhancing web traffic anomaly detection in cloud environments with LSTM-based deep learning models. International Journal in Physical and Applied Sciences, 7(5).

[31] Shahin, O. R., Alshammari, H. H., Alzahrani, A. A., Alkhiri, H., & Taloba, A. I. (2023). A robust deep neural network framework for the detection of diabetes. Alexandria Engineering Journal, 74, 715-724.

[32] Kodadi, S., & Pushpakumar, R. (2020). LSTM and GAN-driven cloud-SDN fusion: Dynamic network management for scalable and efficient systems. International Journal in Commerce, IT and Social Sciences, 7(7).

[33] Kumar, Y., Koul, A., Singla, R., & Ijaz, M. F. (2023). Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. Journal of ambient intelligence and humanized computing, 14(7), 8459-8486.

[34] Bhadana, D., & Kurunthachalam, A. (2020). Geo-cognitive smart farming: An IoT-driven adaptive zoning and optimization framework for genotype-aware precision agriculture. International Journal in Commerce, IT and Social Sciences, 7(4).

[35] Ghosh, M., Lasker, A., Banerjee, P., Manna, A., Obaidullah, S. M., Gonçalves, T., & Roy, K. (2023, November). Plant disease detection and classification using a deep learning-based framework. In International Conference on Intelligent Data Engineering and Automated Learning (pp. 39-50). Cham: Springer Nature Switzerland.

[36] Gudivaka, R. L., & Mekala, R. (2018). Intelligent sensor fusion in IoT-driven robotics for enhanced precision and adaptability. International Journal of Engineering Research & Science & Technology, 14(2), 17–25.
[37] Singh, G., & Yogi, K. K. (2023). Performance evaluation of plant leaf disease detection using deep learning models. Archives of Phytopathology and Plant Protection, 56(3), 209-233.
[38] Deevi, D. P., & Jayanthi, S. (2018). Scalable Medical Image Analysis Using CNNs and DFS with Data Sharding for Efficient Processing. International Journal of Life Sciences Biotechnology and Pharma Sciences, 14(1), 16-22.
[39] Sarkar, O., Islam, M. R., Syfullah, M. K., Islam, M. T., Ahamed, M. F., Ahsan, M., & Haider, J. (2023). Multi-scale CNN: An explainable AI-integrated unique deep learning framework for lung-affected disease classification. Technologies, 11(5), 134.
[40] Gollavilli, V. S. B., & Thanjaivadivel, M. (2018). Cloud-enabled pedestrian safety and risk prediction in VANETs using hybrid CNN-LSTM models. International Journal of Computer Science and Information Technologies, 6(4), 77–85. ISSN 2347–3657
[41] Haridasan, A., Thomas, J., & Raj, E. D. (2023). Deep learning system for paddy plant disease detection and classification. Environmental monitoring and assessment, 195(1), 120.
[42] Parthasarathy, K., & Prasaath, V. R. (2018). Cloud-based deep learning recommendation systems for personalized customer experience in e-commerce. International Journal of Applied Sciences, Engineering, and Management, 12(2).
[43] Salamai, A. A. (2023). Enhancing mango disease diagnosis through eco-informatics: A deep learning approach. Ecological Informatics, 77, 102216.
[44] Dondapati, K. (2018). Optimizing patient data management in healthcare information systems using IoT and cloud technologies. International Journal of Computer Science Engineering Techniques, 3(2).
[45] Shambharkar, P. G., & Sharma, S. (2023, March). Plant disease detection and prevention using deep learning. In 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 1832-1838). IEEE.
[46] Gudivaka, R. K., & Rathna, S. (2018). Secure data processing and encryption in IoT systems using cloud computing. International Journal of Engineering Research and Science & Technology, 14(1).
[47] Mallick, M., Govindaraju, S., Kumar, A. S., Kandasamy, M., & Anitha, P. (2023, February). Analysis of panoramic images using deep learning for dental disease identification. In 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS) (pp. 1513-1517). IEEE.
[48] Kadiyala, B., & Arulkumaran, G. (2018). Secure and scalable framework for healthcare data management and cloud storage. International Journal of Engineering & Science Research, 8(4), 1–8.
[49] Faria, F. T. J., Moin, M. B., Al Wase, A., Sani, M. R., Hasib, K. M., & Alam, M. S. (2023, March). Classification of potato disease with digital image processing technique: a hybrid deep learning framework. In 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 0820-0826). IEEE.
[50] Alavilli, S. K., & Pushpakumar, R. (2018). Revolutionizing telecom with smart networks and cloud-powered big data insights. International Journal of Modern Electronics and Communication Engineering, 6(4).
[51] Liu, F., Yuan, S., Li, W., Xu, Q., & Sheng, B. (2023). Patch-based deep multi-modal learning framework for Alzheimer's disease diagnosis using multi-view neuroimaging. Biomedical Signal Processing and Control, 80, 104400.