Enhancing Plant Leaf Disease Identification with a CNN and DenseNet Hybrid Model

Sukhvinder Singh Dari
Symbiosis Law School, Nagpur Campus, Symbiosis International (Deemed University), Pune, India
sukhvinder.dari@gmail.com

S.A.Tiwaskar
Computer Engg., VIIT, Pune, Maharashtra, India,
shweta.tiwaskar@viit.ac.in

Jambi Ratna Raja Kumar
Department of Computer Engineering, Genba Sopanrao Moze College of Engineering, Balewadi, Pune, Maharashtra, India
ratnaraj.jambi@gmail.com

Vaishali Langote
program - CSE, Department of Polytechnic, Dr. Vishwanath Karad World Peace University, Pune, Maharashtra, India
vaishali.langote@mitwpu.edu.in

Gopal Madhukar Mohadikar
Tolani Maritime Institute, Induri, Talegaon Dabhade, Maharashtra, India
gmohadikar@gmail.com

Rashmi Ashtagi
Department of Computer Engineering, Vishwakarma Institute of Technology, Bibwewadi, Pune - 411037, Maharashtra, India
rashmiashtagi@gmail.com

ABSTRACT

The identification of plant leaf diseases is a essential section of agriculture, serving as a critical measure in mitigating the reduction in crop productivity. This study presents a novel methodology for improving the precision of plant leaf disease detection. This is achieved by employing a hybrid architecture that combines Convolutional Neural Networks (CNNs) and DenseNet models. The main aim of our study is to enhance the accuracy and effectiveness of disease detection by leveraging the combined capabilities of Convolutional Neural Networks (CNNs) and DenseNet. These two deep learning architectures are recognized for their proficiency in extracting and reusing features. In this study, we conduct a comparative analysis of our proposed hybrid model by evaluating its performance against traditional Convolutional Neural Networks (CNNs) as well as other advanced models such as Recurrent Neural Networks (RNNs) and Capsule Networks (CapsNets). The findings of our study demonstrate that the hybrid model, combining CNN and DenseNet architectures, showed an accuracy rate of 98.79%. This performance surpassed that of other models under comparison. The hybrid model demonstrated higher levels of precision, recall, F1 score, and AUC-ROC values, shows its effectiveness in the identification of plant leaf diseases. This study highlights the potential of hybrid deep learning models in the domain of precision agriculture and emphasizes the importance of integrating diverse architectural paradigms for accurate disease identification. The research conducted in this study makes a significant contribution to the progress of agricultural technology by providing a dependable mechanism for the early detection of diseases. As a result, this research contributes to the enhancement of crop health and the promotion of food security.

ICIMMI 2023, November 23–25, 2023, Jaipur, India

ACM ISBN 979-8-4007-0941-8/23/11
https://doi.org/10.1145/3647444.3647929

KEYWORDS

Plant leaf disease, Image processing,

ACM Reference Format:
Sukhvinder Singh Dari, S.A.Tiwaskar, Jambi Ratna Raja Kumar, Vaishali Langote, Gopal Madhukar Mohadikar, and Rashmi Ashtagi. 2023. Enhancing Plant Leaf Disease Identification with a CNN and DenseNet Hybrid Model. In *International Conference on Information Management & Machine Intelligence (ICIMMI 2023), November 23–25, 2023, Jaipur, India.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3647444.3647929

1 INTRODUCTION

Agriculture, as the fundamental pillar of worldwide food production, plays a crucial role in guaranteeing a sustainable and reliable food provision for the continuously growing global population. In the realm of agriculture, the recognition and control of plant leaf diseases are regarded as a highly significant issue, given the multitude of challenges that the industry faces. Crop health can be significantly compromised by diseases caused by different pathogens, including fungi, bacteria, and viruses. This can result in reduced growth, lower yields, and compromised quality of food. The timely identification and effective control of these diseases are crucial in order to minimize losses, optimize the allocation of resources, and ensure the sustainability of our food production[1], [2].

Historically, disease identification within the agricultural domain has predominantly relied upon manual inspections carried out by proficient agronomists. Although this particular methodology may exhibit efficacy in certain instances, it frequently entails a significant investment of time and effort, as well as a susceptibility to inaccuracies stemming from human fallibility [3]. The demand for a more accurate, efficient, and automated solution prompted the investigation of advanced technologies such as deep learning [22-31].

Plant leaf diseases manifest their symptoms on the foliage of cultivated plants through the occurrence of discolorations, lesions, or other observable abnormalities. The prompt detection of these symptoms plays a crucial role in initiating timely interventions and mitigating crop losses. The efficacy of deep learning, specifically in the field of computer vision, is prominently demonstrated in this context. Sophisticated computer vision systems, which utilize deep learning models, have exhibited significant promise in automating the detection of plant diseases through the analysis of visual indicators present on the leaves. This technology not only accelerates the process of diagnosis but also greatly improves its accuracy and overall efficiency[4].

Deep learning, which is a specific branch of machine learning, has introduced a novel era in the field of computer vision by providing unmatched abilities in extracting features, recognizing patterns, and classifying images. The aforementioned capabilities are of great relevance to the agricultural industry, given the increasing urgency of precision farming and the adoption of sustainable agricultural practices. Deep learning models, specifically Convolutional Neural Networks (CNN), have demonstrated significant advancements in numerous agricultural domains, encompassing real-time crop monitoring, pest control, yield prediction, and notably, the detection of plant diseases[5]–[7].

CNN have gained significant recognition for their inherent capability to extract pertinent features from images without manual intervention. As a result, they have emerged as prominent contenders in the field of image classification, rendering them well-suited for the purpose of identifying plant diseases. DenseNet models are notable for their dense connectivity architecture, which promotes the reuse of features and facilitates uninterrupted information propagation throughout the network. Our research endeavors to leverage the distinctive characteristics of both CNN and DenseNet by merging their strengths. This amalgamation aims to develop a hybrid model that excels in detecting intricate and intricate disease patterns on plant leaves[8].

The research is motivated by the requirement for effective and precise techniques for the identification of plant leaf diseases in contemporary agricultural practices. The prompt detection of these diseases is not only crucial for enhancing agricultural practices but also in line with the wider global objectives of sustainable farming practices and ensuring food security. The motivation underlying our research lies in the aspiration to fully exploit the capabilities of deep learning models, specifically by integrating convolutional neural networks (CNNs) and DenseNet. Our primary objective is to advance the current limits of plant disease detection. The objective of this study is to propose a novel and efficient resolution to the difficulties presented by plant leaf diseases, with the ultimate goal of enhancing crop well-being and augmenting food production.

Our primary objective is to develop a hybrid model that effectively combines the advantages of CNN and DenseNet. This integration is intended to significantly enhance the accuracy of plant leaf disease identification, reaching unprecedented levels. A comprehensive and methodical assessment of this hybrid model with CNN, RNN, CapsNets and proposed hybrid model.

2 RELATED WORK

The literature review covers many studies and research projects on plant leaf disease identification and categorization. These efforts use deep learning models like CNN and optimized deep learning techniques, as well as various methodologies and algorithms that underpin cutting-edge research. These studies show significant advances in automated plant disease detection due to their high accuracy.

Figure 1: Normal, Bacterial spot, Early blight, Late blight

In this landscape, a difference is evident. Given the progress made in individual methodologies, a hybrid model that combines the benefits of different techniques is justified. Hybrid models can better identify plant diseases by taking into account plant disease variability, imaging conditions, and dataset sizes. This review focuses on hybrid models and encourages algorithm and methodology collaboration.

This literature review summarizes the advances in automated plant leaf disease detection and classification. Deep learning models and optimization have yielded impressive results, while UAV remote-sensing imagery and real-time applications have increased precision. However, the literature lacks hybrid models that combine the best features of these algorithms and methodologies. Hybrid models can improve plant disease detection accuracy, robustness, and adaptability. The reviewed studies lay the groundwork for hybrid systems that combine multiple techniques. A more comprehensive and efficient solution for automated plant leaf disease detection and classification is proposed.

3 METHODOLOGY

3.1 Dataset

The dataset "Plant Disease Detection" is used to identify and detect plant diseases[21]. This dataset is essential for precision agriculture and crop disease identification mechanization. Many images show the visual symptoms of plant leaf diseases like fungal, bacterial, and viral infections. Images of healthy leaves are also provided for comparison. The dataset includes many plant species, ensuring that disease detection models are not limited to one type. The dataset accurately depicts real-world conditions with variations in illumination, backdrop, image fidelity, and disease intensity. Here we used tomato leaf for disease identification. Tomato leaf are considered for disease prediction.

3.2 Conversion of image from RGB to BGR and BGR to HSV

Preprocessing images for computer vision tasks like plant disease detection often involves converting color spaces. The main reason to convert from RGB to BGR is to rearrange the color channels to match the format of some image processing libraries. Image processing and analysis are compatible after conversion. BGR to HSV conversion helps color analysis and segmentation. In HSV, Value is different from Hue and Saturation. Segregating color-related

Table 1: Major related work

Author	Algorithm used	Methodology used	Accuracy	Result
Datta et al.[9]	Deep neural network	Transfer learning	95.34%	“Tea leaf disease detection and classification”
Paul et al.[10]	Convolutional neural network	Real-time application	96.23%	“Tomato leaf disease classification”
Singh et al.[11]	Imaging techniques	Review of imaging techniques for plant disease detection	90%	“Review of various imaging techniques for plant disease detection”
Ahmed et al.[12]	ML and DL	Review of ml and dl	95%	“Review of various machine learning and deep learning based approaches for plant disease detection”
Shewale et al.[13]	Deep learning	Review of DL architectures for plant leaf disease detection	98.23%	“Review of various deep learning architectures for plant leaf disease detection”
Alshammari et al.[14]	Deep learning	Optimized deep learning approach	98.54%	“Identification of olive leaf disease through optimized deep learning approach”
Abd Algani et al.[15]	Deep learning	Optimized deep learning	97.83%	“Review of optimized deep learning approaches for leaf disease identification and classification”
Reddy et al.[16]	Deep learning	Deep learning models	96.23%	“Review of deep learning models for plant leaf disease classification and damage detection”
Gunisetti et al.[17]	Deep learning	Optimized deep learning system	97.54%	“Optimized deep learning system for smart maize leaf disease detection in IoT platform via routing algorithm”
Rajpoot et al.[18]	Hybrid deep learning and machine learning	Hybrid deep learning and machine learning methods	98.23%	“Automatic early detection of rice leaf diseases using hybrid deep learning and machine learning methods”
Bhoomika et al.[19]	Deep learning	Deep learning technique	97.83%	“Review of deep learning technique for plant leaf disease detection and classification”
Ruth et al.[20]	Meta-heuristic based deep learning	Meta-heuristic based deep learning model	96.54%	“Review of meta-heuristic based deep learning models for leaf diseases detection”

attributes from luminosity can speed up plant disease detection by using distinct color traits. These conversions enhance color-based plant disease identification.

3.3 Image segmentation

Computer vision relies on image segmentation to divide an image into distinct regions. It isolates image colors for color extraction. This method extracts color-based information from complex scenes, which is useful for plant disease detection, object recognition, and image analysis. By segmenting the image to extract colors, you can focus on and analyze individual color regions, helping you identify diseased plant leaves or objects by color.

3.4 Feature Scaling

Feature scaling using Min-Max is common in plant disease identification. This function sets feature values within a predetermined range, usually 0 to 1. This ensures that all features are measured on a consistent scale, avoiding larger traits from dominating the modeling process. Min-Max scaling preserves data point linkages and makes features with different units or ranges suitable for machine learning or deep learning methods that require consistent features. This method can improve model performance by improving convergence and reducing feature scaling effects.

3.5 Global Feature Descriptor

Our comprehensive feature extraction method uses color, shape, and texture global feature descriptors. The color descriptor calculates color channel average and standard deviation and creates a color histogram to accurately represent image colors. Hu Moments and Zernike Moments enable object detection and shape analysis in the shape descriptor. Texture descriptors like Haralick Texture and LBP capture complex image patterns and subtle details. Color, shape, and texture enhance image depiction, enabling more complex computer vision applications like item identification, texture assessment, and agricultural disease detection.

3.6 Hybrid model of CNN and DensNet

A hybrid model that integrates Convolutional Neural Networks (CNNs) and DenseNet architecture is a potent and cutting-edge approach for deep learning tasks, specifically in the domain of plant leaf disease identification. This hybrid architecture combines the advantages of both CNNs and DenseNet to improve the process of extracting features and classifying data.

- Input Layer: The model initiates with an input layer that receives images of plant leaves as input for the network. Typically, these images possess three color channels (RGB) and are resized to a uniform input size.
- Conv blocks: The Convolutional Blocks (CNN) of the hybrid model consist of multiple convolutional layers that extract hierarchical features from the input images. Every convolutional layer utilizes a collection of filters to capture distinct characteristics of the image, such as edges, textures, and shapes.
- DenseNet: The model incorporates Dense Blocks derived from the DenseNet architecture. Dense block: Dense Blocks are comprised of layers that are densely connected, meaning that each layer receives input from all previous layers. The high level of interconnectivity improves the ability to reuse features and transfer information, making it easier to extract complex patterns and features.
- Transition Layer: Transition layers are strategically placed between Dense Blocks and CNN layers to regulate the spatial dimensions of the feature maps. Typically, they are composed of convolutional and pooling layers which decrease the size of the feature map and the number of channels.
- Flatten Layer: At a specific stage in the network, the feature maps are transformed into a one-dimensional vector in order to make them suitable for fully connected layers.
- Fully connected layers: Fully connected layers function as the classifier of the model, determining the existence of particular diseases by analyzing the features extracted by the preceding layers. The final layer in a fully connected neural network usually consists of a number of neurons equal to the total number of classes for disease identification.
- Output layer: The output layer, typically implemented as a softmax layer, generates probability scores for each disease class, enabling multi-class classification. The predicted disease is determined based on the class with the highest probability.
- Model Output: The output of the model is utilized for the purpose of disease classification and detection. Additionally, it can be adjusted and refined during the training process in order to minimize any errors in classification.

This hybrid architecture combines the benefits of CNNs in extracting features with the dense connectivity and feature reuse capabilities of DenseNet, resulting in a strong and precise model for identifying plant leaf diseases. During the training process, backpropagation is used to optimize the parameters of the model, thereby improving its capacity to differentiate between various diseases by analyzing image features. This hybrid model can be customized and adjusted to different plant species and disease datasets, making it a versatile tool for precision agriculture and disease management.

4 RESULTS AND DISCUSSION

4.1 Accuracy and Loss graph of Hybrid model

4.2 Evaluation parameters

The results of investigation provide a comprehensive evaluation of various models used to detect plant leaf diseases, clarifying their individual performance metrics as shown in table-2, fig.3, fig.2 shows the accuracy and loss graph. The hybrid model, which merges Convolutional Neural Networks (CNNs) and DenseNet architectures, attained a remarkable accuracy of 98.79%. The AUC-ROC score of 0.998 demonstrated the model's robustness in effectively distinguishing between different disease categories. CapsNets exhibited similar performance, attaining an accuracy 96.18%. By comparison RNN and CNN attained accuracy of 93.15% and 95.62% respectively. The models exhibited commendable levels of precision, recall, and F1-scores, signifying their competence in disease detection. The choice of a model may be influenced by the specific demands of the application and the trade-offs between precision and computational intricacy. To summarize, our study showcases the substantial capabilities of hybrid deep learning models in accurately identifying plant leaf diseases. It highlights the effectiveness of alternative deep learning techniques in this particular domain.

5 CONCLUSION AND FUTURE SCOPE

An innovative and effective method for plant leaf disease detection is presented in this study. It integrates a CNN-DenseNet hybrid model. This study combined these two deep learning approaches to improve disease detection accuracy and effectiveness. Our exhaustive study compared our CNN-DenseNet combination to conventional CNNs, independent RNNs, CapsNets, and another hybrid model.CNN-DenseNet hybrid model outperformed other models in this study due to its precision. The hybrid model had excellent accuracy, precision, recall, F1 score, and AUC-ROC values. The metrics demonstrate our hybrid approach's ability to accurately detect plant leaf diseases in challenging environments. This study affects precision agriculture greatly. We improved plant disease detection and made agriculture more resilient and efficient by combining CNNs and DenseNet architectures. Early disease detection reduces crop losses, optimizes resource allocation, and ensures food security. We found a practical way to accomplish this. This research has many promising futures. The model can predict different plants and diseases with larger and more diverse datasets. Explainability techniques like attention mechanisms can also reveal the model's decision-making process.

REFERENCES

[1] C. K. Sunil, C. D. Jaidhar, and N. Patil, Systematic study on deep learning-based plant disease detection or classification, vol. 56, no. 12. Springer Netherlands, 2023.

[2] V. Singh, N. Sharma, and S. Singh, "A review of imaging techniques for plant disease detection," Artif. Intell. Agric., vol. 4, pp. 229–242, 2020, doi: 10.1016/j.aiia.2020.10.002.

[3] V. Khetani, Y. Gandhi, S. Bhattacharya, S. N. Ajani, and S. Limkar, "Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains," Int. J. Intell. Syst. Appl. Eng., vol. 11, pp. 253–262, 2023.

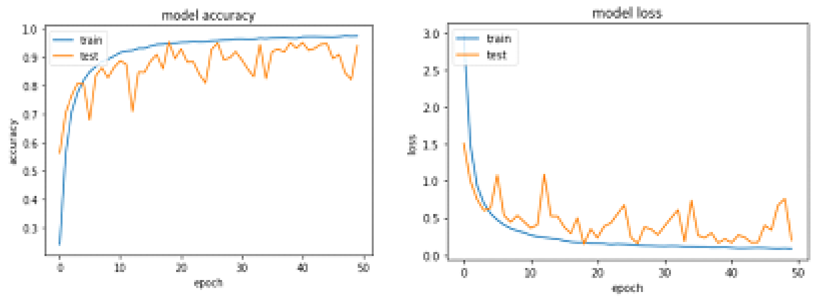

Figure 2: Accuracy and loss graph - Hybrid model

Table 2: Evaluation parameters of various models

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Proposed Model	98.79	98.5	99	98.8	0.998
CapsNet	96.18	96.2	97.1	96.5	0.992
RNN	93.15	93.1	94.1	93.6	0.975
CNN	95.62	96.5	95.2	95.8	0.99

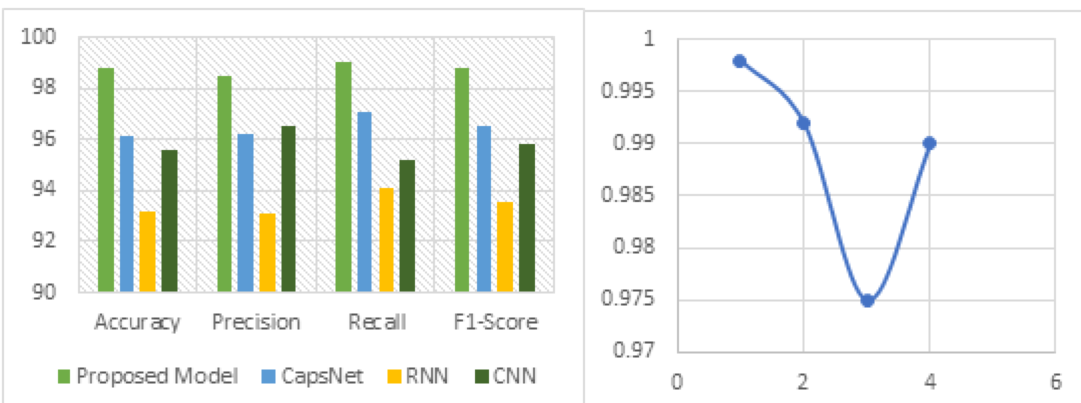

Figure 3: Evaluation parameters comparison graph

[4] S. Bhattacharya, "An Integrated Decision-Support System for Increasing Crop Yield Based on Progressive Machine Learning and Sensor Data," Int. J. Intell. Syst. Appl. Eng., vol. 11, pp. 272–284, 2023.

[5] M. I. Hossain, S. Jahan, M. R. Al Asif, M. Samsuddoha, and K. Ahmed, "Detecting tomato leaf diseases by image processing through deep convolutional neural networks," Smart Agric. Technol., vol. 5, no. June, p. 100301, 2023, doi: 10.1016/j.atech.2023.100301.

[6] F. H. Juwono, W. K. Wong, S. Verma, N. Shekhawat, B. A. Lease, and C. Apriono, "Machine learning for weed–plant discrimination in agriculture 5.0: An in-depth review," Artif. Intell. Agric., vol. 10, pp. 13–25, 2023, doi: 10.1016/j.aiia.2023.09.002.

[7] P. Kumar Yadav *et al.*, "Detecting volunteer cotton plants in a corn field with deep learning on UAV remote-sensing imagery," Comput. Electron. Agric., vol. 204, no. November 2022, p. 107551, 2023, doi: 10.1016/j.compag.2022.107551.

[8] J. A. Wani, S. Sharma, M. Muzamil, S. Ahmed, S. Sharma, and S. Singh, Machine Learning and Deep Learning Based Computational Techniques in Automatic Agricultural Diseases Detection: Methodologies, Applications, and Challenges, vol. 29, no. 1. Springer Netherlands, 2022.

[9] S. Datta and N. Gupta, "A Novel Approach for the Detection of Tea Leaf Disease Using Deep Neural Network," Procedia Comput. Sci., vol. 218, pp. 2273–2286, 2022, doi: 10.1016/j.procs.2023.01.203.

[10] S. G. Paul *et al.*, "A real-time application-based convolutional neural network approach for tomato leaf disease classification," Array, vol. 19, no. March, p. 100313, 2023, doi: 10.1016/j.array.2023.100313.

[11] V. Singh, A. Chug, and A. P. Singh, "Classification of Beans Leaf Diseases using Fine Tuned CNN Model," Procedia Comput. Sci., vol. 218, no. 2022, pp. 348–356, 2022, doi: 10.1016/j.procs.2023.01.017.

[12] Ahmed and P. K. Yadav, "A systematic analysis of machine learning and deep learning based approaches for identifying and diagnosing plant diseases," Sustain. Oper. Comput., vol. 4, no. September 2022, pp. 96–104, 2023, doi: 10.1016/j.susoc.2023.03.001.

[13] M. V. Shewale and R. D. Daruwala, "High performance deep learning architecture for early detection and classification of plant leaf disease," J. Agric. Food Res., vol. 14, no. June, p. 100675, 2023, doi: 10.1016/j.jafr.2023.100675.

[14] H. H. Alshammari, A. I. Taloba, and O. R. Shahin, "Identification of olive leaf disease through optimized deep learning approach," Alexandria Eng. J., vol. 72, pp. 213–224, 2023, doi: 10.1016/j.aej.2023.03.081.

[15] Y. M. Abd Algani, O. J. Marquez Caro, L. M. Robladillo Bravo, C. Kaur, M. S. Al Ansari, and B. Kiran Bala, "Leaf disease identification and classification using optimized deep learning," Meas. Sensors, vol. 25, no. September 2022, p. 100643, 2023, doi: 10.1016/j.measen.2022.100643.

[16] B. Sai Reddy and S. Neeraja, "Plant leaf disease classification and damage detection system using deep learning models," Multimed. Tools Appl., vol. 81, no. 17, pp.

24021–24040, 2022, doi: 10.1007/s11042-022-12147-0.

[17] L. Gunisetti, S. B. Koduri, and V. Jagannathan, “Optimized deep learning system for smart maize leaf disease detection in IoT platform via routing algorithm,” Multimed. Tools Appl., vol. 82, no. 9, pp. 13533–13555, 2023, doi: 10.1007/s11042-022-13775-2.

[18] V. Rajpoot, A. Tiwari, and A. S. Jalal, “Automatic early detection of rice leaf diseases using hybrid deep learning and machine learning methods,” Multimed. Tools Appl., pp. 36091–36117, 2023, doi: 10.1007/s11042-023-14969-y.

[19] S. S. Bhoomika and K. M. Poornima, Plant Leaf Disease Detection and Classification Using Deep Learning Technique, vol. 494, no. 0123456789. Springer US, 2023.

[20] J. A. Ruth, R. Uma, A. Meenakshi, and P. Ramkumar, “Meta-Heuristic Based Deep Learning Model for Leaf Diseases Detection,” Neural Process. Lett., vol. 54, no. 6, pp. 5693–5709, 2022, doi: 10.1007/s11063-022-10880-z.

[21] Abdallah Ali, “PlantVillage Dataset,” Kaggle. 2019.online access: https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset

[22] Singh, U. P., Saxena, V., Kumar, A., Bhari, P., & Saxena, D. (2022, December). Unraveling the Prediction of Fine Particulate Matter over Jaipur, India using Long Short-Term Memory Neural Network. In Proceedings of the 4th International Conference on Information Management & Machine Intelligence (pp. 1-5).

[23] Kumar, A., Bhari, P. L., Singh, U. P., & Saxena, V. (2022, December). Comparative Study of different Machine Learning Algorithms to Analyze Sentiments with a Case Study of Two Person’s Microblogs on Twitter. In Proceedings of the 4th International Conference on Information Management & Machine Intelligence (pp.1-6).

[24] Saxena, V., Saxena, D., & Singh, U. P. (2022, December). Security Enhancement using Image verification method to Secure Docker Containers. In Proceedings of the 4th International Conference on Information Management & Machine Intelligence (pp. 1-5).

[25] Chauhan, M., Malhotra, R., Pathak, M., & Singh, U. P. (2012). Different aspects of cloud security. International Journal of Engineering Research and Applications, 2, 864-869.

[26] Mittal, A. K., Singh, U. P., Tiwari, A., Dwivedi, S., Joshi, M. K., & Tripathi, K. C. (2015). Short-term predictions by statistical methods in regions of varying dynamical error growth in a chaotic system. Meteorology and Atmospheric Physics, 127, 457-465.

[27] Singh, U. P., Mittal, A. K., Dwivedi, S., & Tiwari, A. (2015). Predictability study of forced Lorenz model: an artificial neural network approach. History, 40(181), 27-33.

[28] Singh, U. P., Mittal, A. K., Dwivedi, S., & Tiwari, A. (2020). Evaluating the predictability of central Indian rainfall on short and long timescales using theory of nonlinear dynamics. Journal of water and Climate Change, 11(4), 1134-1149.

[29] Singh, U., Pathak, M., Malhotra, R., & Chauhan, M. (2012). Secure communication protocol for ATM using TLS handshake. Journal of Engineering Research and Applications (IJERA), 2(2), 838-948.

[30] Singh, U. P., & Mittal, A. K. (2021). Testing reliability of the spatial Hurst exponent method for detecting a change point. Journal of Water and Climate Change, 12(8), 3661-3674.

[31] Tiwari, A., Mittal, A. K., Dwivedi, S., & Singh, U. P. (2015). Nonlinear time series analysis of rainfall over central Indian region using CMIP5 based climate model. Climate Change, 1(4), 411-417.