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A Systematics Review and Visualization on IoT based Smart Agriculture Farming using Deep Learning

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Abstract: India's agriculture sector is one of its most valuable industries. At present environment farmer are facing lots of disease on crops and plant. Also, agriculture is one of the major occupations that contribute to prevail over food scarcity. A higher yield in cultivation is considered a success and a lesser yield in cultivation will affect the revenue of a developing country in the field of agriculture. In fact, the utilization of fertilizers in an improper manner by farmers is one of the common reasons for the deficiency of nutrients in the soil, fertilizers should be added in a relevant quantity when there is a lack of nutrients in the soil. Therefore, before using fertilizer it is necessary to examine soil nutrients that are needed for plant growth, soil testing has been done in order to estimate the nutrients present in soil for the growth of plants. For modernization in the field of agriculture smart agriculture has the ability to assist farmers in many ways, recently Internet of Things (IoT) has a great impact on agricultural applications. Recently the search history data from Google has demonstrated that IoT as well as big data was mostly utilized by users in the previous years, but AI has remained an area of interest for over a decade. In this Statistical and Network analysis a total count of 2102 document from smart farming obtained from the Scopus database from PubMed and 40 research paper from the different Scopus journal. VOS viewer was used as network and Statistical analysis tools to study the various aspects of deep learning-based methodology in the crop and plant health disease prediction. The primary objective of databases is statistical analysis of factors such as the number of documents each year, authors' correlation, documents per nation, and sources of publishing. We come to the conclusion that there is a great deal of room for future research in the field of smart farming about early illness prediction using statistical and network analysis.

***Keywords:* Smart farming, Deep learning, Internet of Things, Disease Prediction.**

I. INTRODUCTION

Neural network-dependent models been developed recently for smart farming that use a threshold value of water stress levels to estimate water usage. While current machine learning techniques outperform physical models in terms of performance, they lack resilience under varying climatic circumstances [19] [20].

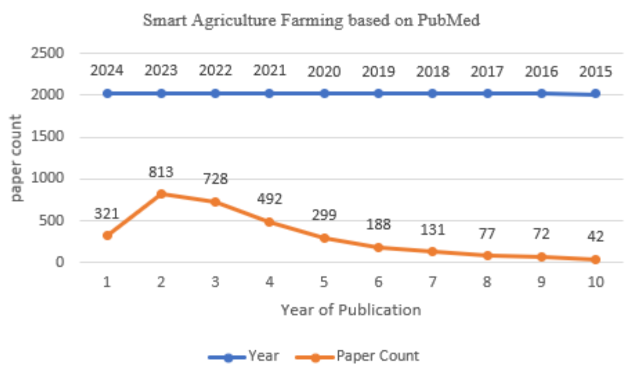

Fig 1: Smart Agriculture Farming based [PubMed].

Online sensor-based infrastructure is not able to provide the data related to the changes in frequency, damaging agricultural yields but gathers the data and presents enough information to make better decisions for the upcoming year's crops or for overcoming future yields [19].

As per the fig 1, in the research smart agriculture farming based on PubMed database were taken past decade year records in that top three year that is 2023, 2022 & 2021 where published research documents are 813, 728 and 492. In this case, we may state that farmers are also using modern instruments and technologies to anticipate plant health and crops ahead of time.

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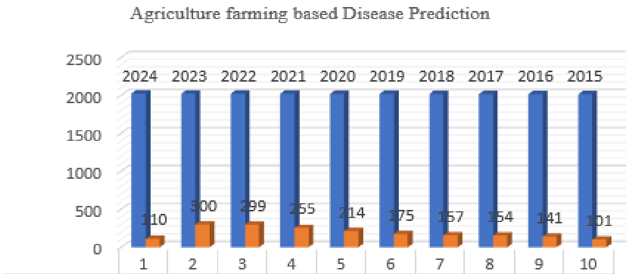

	1	2	3	4	5	6	7	8	9	10
Year	2024	2023	2022	2021	2020	2019	2018	2017	2016	2015
Paper Count	110	300	299	255	214	175	157	154	141	101

Fig 2: Agriculture farming based Disease Prediction [PubMed].

II. Literature Review

Zhao Yafeng and others [1] Plant diseases may be successfully identified from plant leaves. Nonetheless, the quantity of photos depicting damaged leaves gathered from diverse plants is typically out of proportion. Identifying illnesses with a dataset this imbalanced is challenging. To balance such datasets, we created pictures of ill plant leaves using Double GAN, a double generative adversarial network. We suggested creating high-resolution photos of sick leaves with Double GAN by utilizing fewer samples. There are two stages in Double GAN. We utilized both healthy and ill leaves as inputs in stage 1. Initially, the pretrained model was obtained by feeding the WGAN (Wasserstein generative adversarial network) with photos of healthy leaves. Next, the pretrained model was trained on unhealthy leaves to provide 64*64-pixel pictures of the leaves. In order to increase the size of the imbalanced dataset in stage 2, appropriate 256*256-pixel pictures were produced using a super resolution generative adversarial network (SRGAN). at last contrasted with images generated by a DCGAN, or deep convolution generative adversarial network. In addition to expanding the dataset and producing clearer images than DCGAN, double GAN also improved the accuracy of plant species and disease detection to 99.53% and 99.80%, respectively. The identification results are better than those from the first dataset.

Liu Zhiyan and others [2] A major danger to agricultural production and sustainable growth is crop plant disease. Proactively combating the disease's assaults through early disease prediction aids in the disease's successful control. Precision Agriculture (PA) applications rely heavily on modern information and communication technologies (ICTs) to promote sustainable growth. Solutions for the early disease attack prediction are desperately needed in order to prevent plant disease attacks. Only after the disease has shown itself can the current computer vision-based method to disease diagnosis identify its presence. The objective of this study is to build a machine learning (ML) system for early disease attack probability prediction based on directly sensed agricultural field environmental data from the Internet of Things (IoT). The life cycles of plant diseases are significantly correlated with environmental conditions. Environmental conditions in crop fields predict the occurrence of plant diseases. Multiple Linear Regression (MLR) is employed as the machine learning model since there is a linear relationship between disease attack and environmental factors. Plant disease incidences may be accurately predicted by using machine learning techniques based on Internet of Things (IoT) environmental parameters in agricultural fields. The recommended model is used to forecast blister blight (Exobasidium vexans) for the tea (Camellia sinensis) plant in order to assess the effectiveness of the recommended treatment. The use of the proposed model from 2015 to 2019 demonstrates that it is possible to forecast the disease's prevalence in 2019 with up to 91% accuracy.

Himansu Das and others [4] NB, KNN, DT, SVM, and RF are a few of the supervised machine learning algorithms used in this work to identify various illnesses of maize leaves. Following the recommended method, tagged image data was used to train the classification model. Out of all the classification models, the RF classifier has the highest documented accuracy when it comes to identifying illnesses from photo data. In order to prevent illnesses in maize, farmers can take the appropriate action depending on diseases identified as soon as possible. However, there are certain drawbacks to each model used in the classification process, and certain models might not work with all datasets. These models can be used in the future with several high-dimensional data sets and various categorization techniques.

Patil Bhushan et al. [6] In order to detect environmental changes, this model established a novel computational technique that would identify the process of disease detection using photographs of the cotton plant and an Internet of Things-based platform that collects various sensor data. Cotton plant detection and classification are carried out using a deep CNN model, covering every step of the procedure from pre-processing to fine-tuning. In order to generate cost-effective and autonomous new systems, many test cases are completed by continuously monitoring the developed model's performance. Thus, the precision and efficiency of this new technology will lead to an increase in agricultural productivity. By combining sensors and an Internet of Things platform, smart farming monitors field conditions remotely to automate the irrigation system and increase agricultural yield. It will take more time and effort in the future to anticipate cotton plant illnesses using this new technology, despite its increased effectiveness.

Nermeen Gamal Rezk et al. [16] proposed a prediction model that combines conditional random field (CRF) and hybrid convolutional neural network (CNN) to identify the sick portion of the leaf. The model uses a SegNet model, which has the capability to identify both the labelled and pattern of the leaf and a semantic segmentation technique, which is used in the model is more suitable for real time segmentation problems. But the ground truth of the datasets used for evaluation omits the key edges that are crucial to identify the precise location of the disease and its effects, which could cause algorithms to operate incorrectly.

An IoT based plant disease detection technique is developed by Monalisa Mishra *et al.* [22] using sine cosine algorithm-based rider neural network (SCA based RideNN) classifier for the detection of plant diseases. The suggested technique makes it simple for farmers to detect the

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contaminated plants on their property. This method reduces the need for laborers by remotely monitoring the farm from any location with an Internet connection. It minimizes agricultural loss by identifying disease-affected plants at the earliest stage. But the suggested technique is limited to determining if the plant is diseased or not.

Yafeng Zhao [23] presented a double GAN (double generative adversarial network) approach to detect plant diseases and to generate high resolution images of unhealthy plant leaves. The method addresses the issue of unbalanced dataset and can apply to various types of plant diseases but the dataset used in this research is limited to specific type of plant species, so further research is needed to validate the effectiveness of the approach.

Sowmiya M and Krishnaveni S. [21] developed an improved quantum whale optimization with principle component analysis (IQWO-PCA) approach to detect plant diseases. The method reduces the low rate, improves the crop yields and prevents the dangers related to cultivation but the method is only limited to identify tomato diseases and requires more enhanced work for the detection of other crops.

For plant disease detection, A IoT integrated deep learning method called Custom-Net is presented by Nidhi Kundu *et al*. [24]. The model achieves a significant decrease in the number of trainable parameters and training time. Even though the dataset is very small, the method achieves high classification accuracy and the low training time proves its usability in real life systems.

Zhiyan Liu et al. [25] proposed the use of Multiple Linear Regression (MLR), a Machine Learning (ML) approach, to forecast disease attack risk early on using IoT-directly recorded agricultural field environmental factors. The method provided accurately predicts the chance of blister blight disease of tea developing prior to the occurrence of the disease attack, despite potential overfitting issues.

Rabbia Mahum et al. [26] demonstrated the use of an efficient Dense Net model for the detection of potato leaf disease. The computational complexity is reduced by the model's additional transition layer, which also reduces the size of the feature map. While the method addresses the problem of class inequality, it is not suitable for resolving complex issues.

Chowdhury, Muhammad E. H. et al. [7] The majority of the world's food comes from plants. Plant diseases are a contributing factor to lost output, although they may be prevented with ongoing observation. Manually tracking plant diseases takes time and is prone to error. Early detection of plant diseases with artificial intelligence (AI) and computer vision can help to reduce their detrimental effects and get beyond the constraints of continuous human observation. In this work, we propose to use 18,161 segmented and plain tomato leaf pictures to detect tomato ailments using a deep learning architecture based on a recently built convolutional neural network termed Efficient Net. For the segmentation of leaves, the effectiveness of two segmentation models—U-net and Modified U-net—is presented. The models' relative performance is also shown for the following three scenarios: binary (healthy and unhealthy leaves), ten-class (healthy and various categories of unhealthy leaves), and six-class (healthy and diversified groupings of sick leaves). The improved U-net segmentation model showed accuracy, IoU, and Dice score of 98.66%, 98.5%, and 98.73%, respectively, for the segmentation of leaf image data. EfficientNet-B7 performed quite well, achieving 99.95% and 99.12% accuracy for binary classification and six-class classification using segmented photos, respectively.

In the end, EfficientNet-B4 used segmented pictures to classify 10 classes with an accuracy of 99.89%. It is reasonable to assume that all of the designs outperformed in terms of disorder classification when trained with deeper networks using segmented images. Each of the experimental studies presented in this article outperforms earlier studies conducted in the same field.

Sharma, Vikas, et al. [10] In the proposed study, we developed an interface for identifying five distinct forms of illness in rice crops using the Matlab tool. In the first step, leaves that are ill or infected are identified by first turning the picture into a grayscale one and then using a median filter to eliminate noise. In the following stage, several feature vectors are used to identify (classify) the diseased area of the rice leaf using MDC and Bayes' classifier. We found that MDC outperforms Bayes' classifier in terms of accuracy, with MDC achieving superior results—roughly 81%—while Bayes' classifier produced results closer to 69%.

2.1 Problem Statement:

For the identification of plant illnesses using deep learning, there are concerns in existing approaches such as difficulty in reliable detection of plant disease in complicated backdrops, the necessity of high computing time, and the overfitting issues. Therefore, the goal of this research is to create a quicker deep BiLSTM model based on Artificial Coyote optimization in order to address these problems and accurately detect plant illnesses.

III. Network Analysis

Using the VOS viewer software tools, all 2102 retrieved papers are analyzed in the network analysis of the Scopus-based PubMed database. The efficiently offers network analysis of coauthorship. co-citations and co-occurrences as well as bibliographic coupling. Database analysis is done using VOS viewer software tools in addition to Scopus and PubMed database analysis.

An effective tool for analyzing citations in terms of source, authors, organizations, nations, keyword co-occurrences, couplings bibliographies, and other aspects is the VOS viewer programme. The many types of analysis done on agricultural disease prediction available in the Scopus and PubMed databases are represented diagrammatically in the following.

A. Co-authorship Analysis

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Analysis between Co-authorship and authors at agriculture disease prediction (PubMed Database).

There are 12764 writers altogether, with a minimum of five documents per author and a total threshold value of 43. The overall strength of the co-authorship ties with other writers will be computed for each of the 43 authors. The writers with the strongest overall links will be chosen. There are now 43 writers to choose from, 5 of whom are related.

Fig 3: "Co-authorship Network Analysis in Terms of Authors".

Analysis of Network of Co-authorship in terms of organization:

The minimal number of publications generated by an organization is taken into consideration in this network analysis of co-authorship and organisation, which makes use of the PubMed database as a resource. A maximum of 25 organizations per document should be chosen. Now, we need to choose four minimal papers from each of the 7162 organizations we located; seven of them match the requirement. The overall strength of the co-authorship ties with other organizations will be computed for each of the seven organizations. The companies with the strongest overall links will be chosen.

Fig 4: Analysis between Co-authorship and Organization.

Co-occurrence Analysis:

Analysis of Network between Co-occurrence and all keywords:

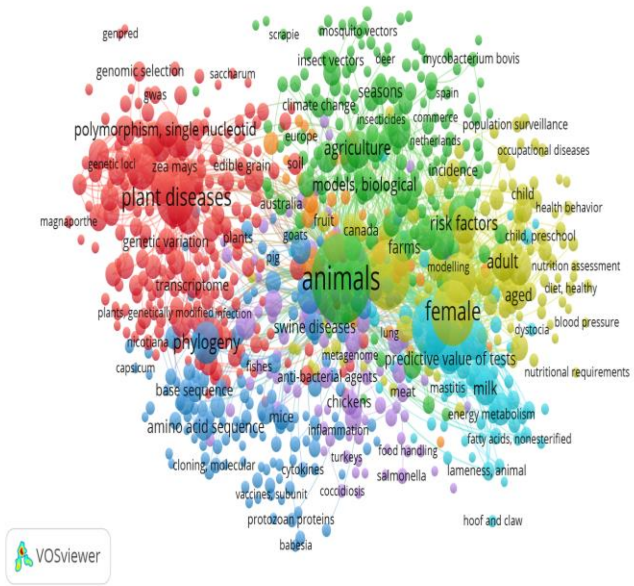

Fig 4: Analysis between Occurrence with All Keywords.

The minimal number of occurrences of a keyword is five, and out of the 8282 keywords, 814 fulfil the threshold in this network study on agriculture disease prediction in deep learning between co-occurrence and keyworks utilizing the Scopus-based PubMed database. The overall strength of the co-occurrence linkages with other keywords for every term will be computed. The highest combined link strength keywords will be chosen. where 814 keyworks were chosen.

Analysis of Network between Co-occurrence and all Authors:

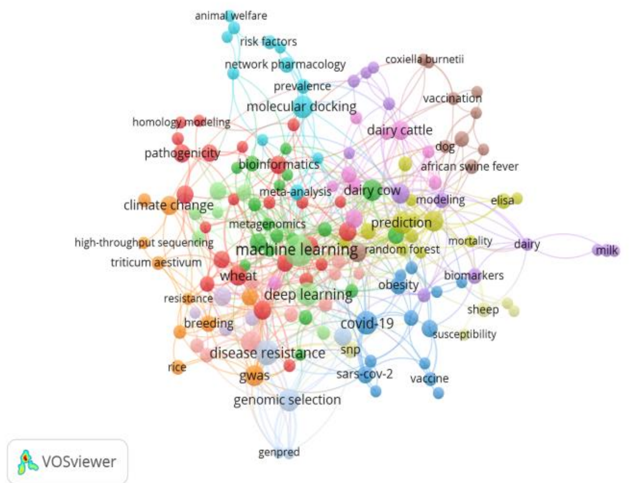

Fig 5: Analysis between co-occurrence with Authors Keywords.

The minimal number of occurrences for a term in this network study of smart farming, agriculture-based disease prediction in deep learning between co-occurrence and authors using the Scopus-based PubMed database is five. Out of the 5485 keywords, 156 fulfil the criterion. The overall strength of the co-occurrence linkages with other keyworks will be computed for each of the 156 keywords. The highest combined link strength keywords will be

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chosen. where 156 keywords were chosen. where there are 155 things in the greatest collection of related objects.

Analysis of Network between Co-occurrence and MeSH Keywords:

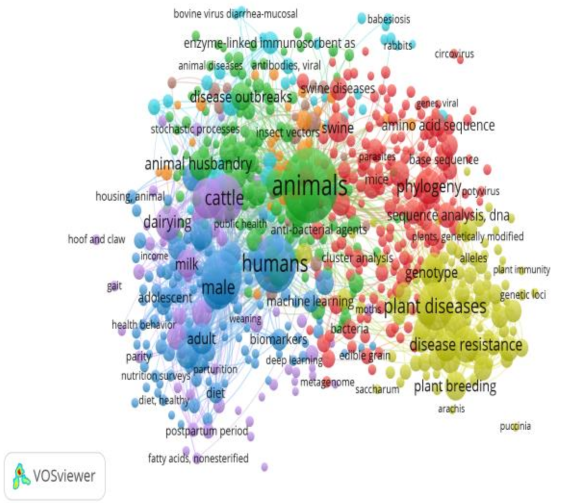

Fig 6: Analysis of Network between Co-occurrence and MeSH Keywords.

Statistical Analysis between co-occurrence with All keywords:

In this proposed research article, to analyze the cooccurrence with the all-author keywords, where we found highest 3 occurrence that are nothing but the machine learning, disease resistance and the Deep learning.

Table 1: Analysis between Occurrence with authors keywords.

Sr. No	Keyword	Occurrences	Total Link Strength
1	Machine Learning	48	20
2	Disease Resistance	28	18
3	Deep Learning	24	12
4	Covid-19	23	4
5	Prediction	22	12
6	Genomic Selection	21	12
7	Genomic prediction	20	13
8	Dairy Cow	19	5
9	Cattle	17	6
10	Gwas	17	9
11	Epidemiology	16	2
12	Wheat	16	6
13	Dairy Cattle	15	2
14	Artificial Intelligence	13	6
15	Bioinformatics	13	1

IV. Conclusion

In this research article an IoT based smart farming method is proposed in this research using a novel deep learning method named artificial coyote optimization based faster deep BILSTM to analyze and detect the plant diseases and the soil information. Here, IoT sensors are used to collect the data and stored the collected data for expert analysis. It uses datasets from plant village and soil fertility datasets. Artificial coyote optimization which is the hybridization of artificial rabbit and coyote optimization improves the performance of the Deep BiLSTM model. This systematic review-based research article we taken article or data from the Scopus journal and PubMed these are one of the types of research based largest databases in the world, are used for systematic literature review, bibliometrics analysis and visualization of work done so far in the field of smart agriculture-based farming using machine learning and deep learning. We have taken in account of Scopus and PubMed documents released between 2015 to 2024 up to 12 may 2024. By using the keywords search the database searching done. In this analysis a total count of 2102 document from smart farming obtained from the Scopus database from PubMed and 40 research paper from the different Scopus journal. In assessing the aforementioned database, specific factors are duly taken into account. It is important to note that practically the whole essay is written in standard English. According to PubMed database statistics, 2023 is the year with the most published articles, followed by 2022. Almost all document categories are published through conferences, and a higher percentage of papers are published in research journals.

Network analysis was also facilitated by VOS Viewer software tools. The same database is used for other analytical shows, including co-authorship and co-occurrences analyses. As stated above, these various networks provide a wealth of information on the aforementioned distinctions. Additionally, it is evident that much of the work being done to implement smart farming practices—which use deep learning technology to anticipate crops and plant-based diseases—is focused on this aspect. In order to visualize significant contributions to the field, these preliminary efforts map the relationships between the most well-known publications published. A significant amount of work in this area is anticipated in the upcoming year.

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