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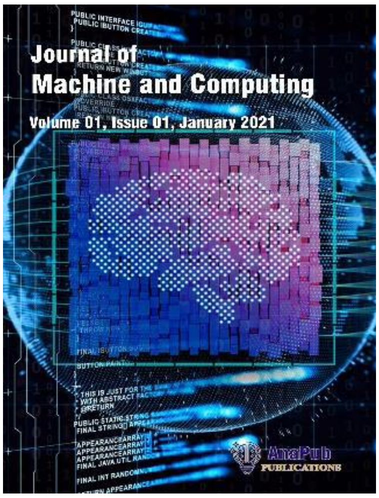

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Enhancing Agricultural Productivity: IoT and Attention-Based CNN-BLSTM for Fine-Grained Crop Disease Detection

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Abstract

A more efficient food production system is essential in all industries, but notably agriculture, to meet the needs of world's growing population. However, there will be times when supply and demand are out of sync. One of the most difficult and time-consuming tasks in increasing agricultural output is managing and maintaining human and financial resources. In terms of increasing food production, managing resources, and manpower, smart agriculture is the way to go. to develop an IoT system for identifying crop diseases at a finer grain size by combining IoT with deep learning. This technology has the capability to identify agricultural diseases autonomously and provide farmers with diagnostic data. The research suggests a model for fine-grained disease diagnosis in the system called an attention-based convolution neural network with bidirectional long short-term memory (ACNN-BLSTM). The suggested approach incorporates a compensation layer that use a compensation algorithm to combine the outcomes of multidimensional recognition. It does this by first identifying in three dimensions: species, coarse-grained disease, besides fine-grained disease. The ACNN-BLSTM model's hyperparameters are fine-tuned using a hybrid approach called SA-GSO, which combines simulated annealing with glowworm swarm optimisation. This improves the model's detection performance. In comparison to other well-known deep learning representations, the studies demonstrate that the suggested neural network outperforms them in terms of recognition effect and usefulness for teaching real-world agricultural production tasks..

Keywords: Internet of Things; Attention-based convolution neural network; Glowworm swarm optimization; Simulated annealing; Agriculture; Crop Disease.

Introduction

The goal of modern agricultural practices is to cultivate crops in carefully managed spaces, like greenhouses, that can either increase plant yields or mimic the weather patterns of certain regions so that imported goods can be grown locally [1]. A thorough implementation of modern monitoring cellphones, can also help farmers minimise the negative effects of weather and disease changes on agricultural yields and quality [2]. Thanks to recent advancements, farmers can now assess their crops' health with great precision and make informed decisions about irrigation, climate change, and soil nutrition [3]. This allows for more efficient automation of management tasks, higher crop yields, and less environmental damage [4]. Agronomists and farmers have started using technology to make greenhouse operations more efficient [5]. In order to remotely monitor their crops and equipment, grasp the complete management state properly through statistical analysis, and tell the robots to carry out agricultural chores, they use smartphones and the data acquired and communicated by the Internet of Things (IoT) to do so [6]. The present state of artificial intelligence (AI) in agricultural machinery and systems is inadequate to accomplish fully automated operations [7] and management with minimal oversight to maximise output while taking variability and uncertainties into account within precision agriculture (PA) [8]. Nevertheless, greenhouses are making good use of this integration of technologies with efficient human intervention.

To maximise the PA's economic value, intelligence is seen as both a key technological challenge and an additional facilitator [9]. With the advent of deep learning technology, numerous areas of PA have become much easier to manage and make decisions about. This includes visual crop categorisation [10], real-time plant disease and pest recognition [11], autonomous robots for picking and harvesting [12], and monitoring the growth of crops for quality and health [13]. And with the proliferation of data-gathering devices like smartphones, cameras, and sensors, deep-learning algorithms are poised to make significant strides in the agriculture sector in the not-too-distant future [12]. Deep learning is based on the way the human brain processes visual information, which involves multiple levels of abstraction. It enables computational models with many processing layers to learn these representations by utilising non-linear modules, such as memory units, which take the raw input as input and transform it into a slightly more abstract representation at each level [13]. Agricultural tasks can be automatically completed with the synthesis of enough such transformations, allowing for the learning of very complex functions and the discovery of challenging structures in high-dimensional data.

In contrast to their state-of-the-art performance in other areas of study, deep-learning networks are not well-suited to the irrigation, picking, pesticide spraying, and fertilisation tasks that are integral to crop management in agriculture [14]. The lack of publicly available benchmark datasets tailored to different agricultural missions is the primary reason why deep-learning technologies and the advancement of greenhouse intelligence have been set back [15]. These cases highlight the importance of building suitable crop datasets by making full use of different gathering devices for broader and deeper networks to produce superior outcomes. The first stage in preventing diseases is rapid and precise identification [16]. Damage can be mitigated and less drastic steps can be taken when detected early. If crop illnesses are wrongly recognized, then treatments may be inefficient or even damaging to crops. Manual approaches are primarily used to identify crop diseases worldwide, particularly in underdeveloped nations [17].

To have developed an agrarian IoT scheme for identification by combining deep learning with IoT technology. Our goal is to make a positive impact on agricultural production. to built the ACNN-BiLSTM with the SA-GSO algorithm for the IoT system's deep learning module. In real-world agricultural production activities, our model is instructive since it can detect the severity of crop diseases compared to current methods of disease identification. In a timely manner, this technology can gather data on crop diseases and relay it to farmers. to fine-tune the network model by modifying the residual network's optimisation and initialisation processes. to build the model to detect agricultural diseases with a finer degree of specificity.

In ensuing sections of the paper, to will go over the relevant literature, present our IoT system and the model that is suggested in this article, analyse the experimental results, and then present our conclusions and recommendations for future research.

2. Related works

A new hybrid blockchain system called RENECBCB was developed by Mahalingam and Sharma [18] to safely store the detected agricultural data on a cloud server. All of the data came from a regular old website. Following the pre-processing step, this model passes the filtered input dataset on to the field monitoring module. The offered method's monitoring system extracts useful features and enables continuous monitoring. In order to prevent unauthorised parties from accessing the extracted features, cryptoanalysis was also performed. The data was subsequently saved on the cloud server using encryption. In addition, assaults were launched on the cloud server to conduct security analysis, with findings estimated in two situations, one before and one after the attack. Following its implementation in Python, the given model achieved an accuracy of approximately 97.7 percent, a confidentiality rate of about 97.[illegible]%, and an execution time of approximately 2.7 milliseconds for encryption, 2.6 milliseconds for decryption, and 11 milliseconds for the overall process. In addition, the suggested model reduced the error rate to approximately 0.0227%. There was a comparison between the computed results and the current security methods.

A thorough framework for smart farming has been proposed by Rehman et al., [19]. Three technological integrations make up the proposed framework: 1) an effective combination of battery energy storage systems (BESS) with renewable energy resources (RERs); 2) a precision irrigation system operated by an android app that monitors the environment; and 3) a robotic system that applies chemicals to specific areas. In order to examine and evaluate best-case scenarios including various energy sources, the suggested framework examines a case study on Sharjah, UAE. to successfully integrated multiple prototypes using the Blynk IoT platform, which gave users a uniform boundary. The findings also offer a thorough examination of the interactions between the grid and RERs in different configurations. The results show that this framework has the ability to greatly improve farming practices in terms of sustainability, efficiency, and technology. In addition, it is a step towards a more sustainable and intelligent agricultural future by providing a comprehensive answer to the problems facing modern agriculture.

Performance, scalability, adaptability, , extensibility, and security are some of the quality features that Mishra et al., [20] has identified and addressed. They have also mapped these traits to relevant IoT-based farm software architecture. Also, some difficulties were recognised and explored for the software architectural quality of IoT-based agriculture schemes, can help in planning, implementing, and improving agricultural systems that rely on the IoT to meet the evolving needs of the agricultural sector.

An innovative and enhanced method that allows plants to converse with humans via the IoT is suggested in a work by Kaur et al. [21]. To make sure the plants are healthy, it's important to track and categorise their related parameters. The suggested system uses the IoT and a sum of sensors to track the needs of plants. Environmental sensors gather data, which is then transmitted to the user's Android app on their smartphone. After this, the data is analysed to determine if the plant is healthy or not. The proposed framework outperforms the current classifiers utilised in previous studies in terms of accuracy (89.85%), precision (88.37%), besides recall (86.55%), all achieved through the use of the machine learning classifier Random Forest (RF).

A cloud-based smart irrigation scheme has been introduced by Et-taibi et al., [22] to link multiple small-scale smart farms and consolidate relevant data. By collecting, storing, and analysing large amounts of data, the system maximises the efficiency of irrigation water utilisation. In dry areas in particular, this data can help with water management decisions, which in turn can encourage conservation measures. Additionally, this project studies weather prediction services to increase intermittent wet times, within a real-world testbed powered by solar energy. The testbed is equipped with an advanced technology for managing massive data. Displayed here is a model of a Smart Farm that makes use of IoT, embedded systems, cheap WSNs, an NI CompactRIO computing. The results show that there are noticeable increases in water saving, which is encouraging. In addition, the study's deployment methodology offers a straightforward road map that may be easily adjusted for future projects.

One method for remote, real-time pest identification that makes use of IoT and DL architectures is proposed by Dhanaraj et al. [23]. The IoT and DMF-ResNet, part of the integrated pest detection approach, are the major components that make up the construction of the remote pest detection system. Insect and rodent noises are used to train the DMF-ResNet method for pest detection. The results of this potential of the IoT and artificial intelligence (AI) for field-based pest monitoring, and they show that humans are nearly unnecessary for constant vigilance. The proposed DMF-ResNet technology accurately automate the finding based on studies in vast agricultural areas. It pest identification than the traditional methods used by DenseNet, VGG-16, YOLOv5, DCNN, ANN, KNN, ResNet-50, with a score of 99.75%, sensitivity of 98.64%, specificity of 98.48%, recall of 99.08%, precision of [illegible], and an F1 score of 99.11%.

3. Proposed Methodology

In this work, the crop leaves that is collected from agriculture land is used to detect disease by using advanced deep learning model, where Figure 1 demonstrations the working flow of the proposed perfect.

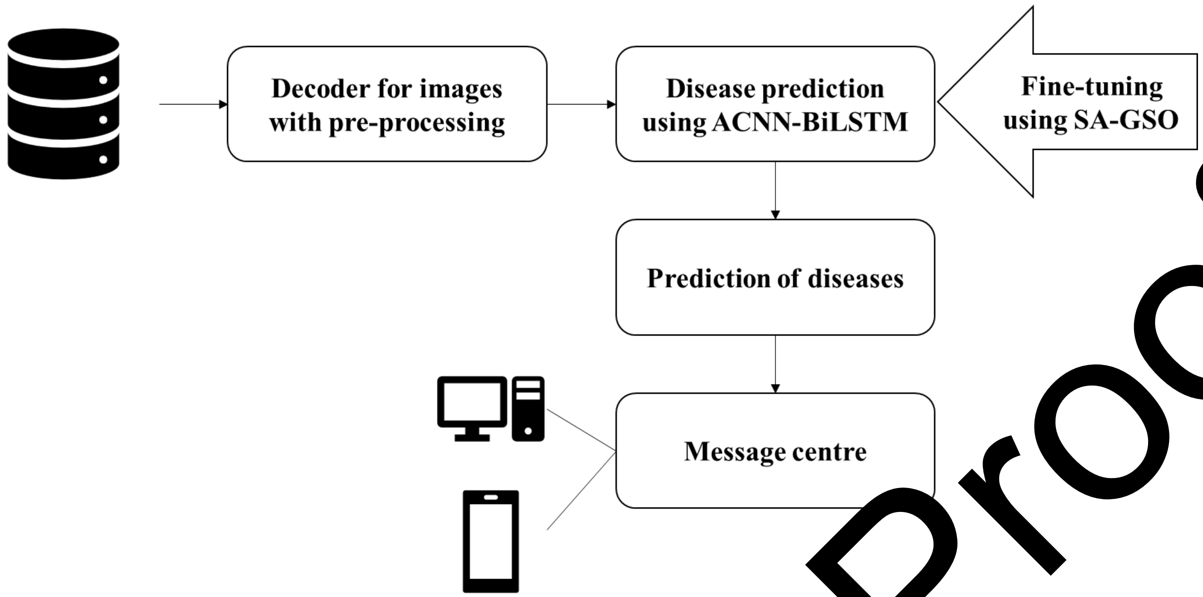

Figure 1: Workflow of Research Prototypical

3.1. System Structure

Intelligent terminal devices, video cameras, and deep learning models make up the proposed Internet of Things system. Cameras are used by the system to gather cropped videos. It analyses crop health using deep learning models and then relays that information to farmers via smart terminal applications, which can be web apps or smartphone apps. The six components that make up the system are as follows: a terminal (computer or smartphone), a message centre, a deep learning model, a decoder, and one or more video cameras. These are the primary roles that each par plays in the system's operation::

- The video camera is installed in greenhouses or crop fields in order to gather data about the crops. In most cases, we'll install a number of video cameras.
- The crop image can be extracted from the decoded information stream by using the decoder, which can receive data from numerous video cameras and decode it.
- The decoder transmits the crop image to the deep learning model, which then uses the learnt model to determine the crop's health state and sends the result to centre.
- The results of the discrimination are received by the message centre, which then organises and handles them using the message queue that the processor employs.
- The processor receives data from the message centre, performs processing on the data, and then notifies the web app and smartphone app..

An integral aspect of the system, deep learning models have a direct impact on how well the IoT scheme functions. Most current crop disease identification schemes can only name the various illnesses that affect crops; they can't tell you which ones specifically. Crop disease severity varies, though, in the context of actual agricultural production. This means that not only is the dosage of medication different, but so is the treatment approach. When it comes to treating diseases, lowering pesticide use, and safeguarding crops and the environment, fine-grained disease diagnosis is instructive. Accordingly, the research suggests a modified LSTM model for the system's model; this model is better able to detect common and severe crop diseases and is more stringent in real-world agricultural production operations. Here to will go over the proposed model in great depth..

3.2. Data Collection and Processing

The data set used in this investigation is available from AI Challenger [24]. There were 59 categories, broken down as follows: 10 species, 49 illness types with extensive descriptions, and 10 health-related categories, with a 36,258 images. Each image was collected from a crop in a natural context and modified with only one leaf.

Various factors, including variations in crop species, shooting conditions, equipment, and picture sources, rendered the dataset unfit for use in image classification. Issues with picture recognition arise from significantly different picture types, variable picture sizes, and uneven picture quality. to processed the dataset prior to training the model in order to resolve these issues. There were three main components to the process: data normalisation, data augmentation, and SVD. The issue of large disparities in the quantity of images across the different categories is addressed in the first stage of data augmentation. The largest category comprises 2473 photographs, and the smallest 22 images. The training of the model is affected by the quantity of photos in categories, which in turn reduces the test accuracy.

In order to make perfect training easier, the second stage in data normalisation is to make all the photos the same size. Before the experiment, to made sure that all of the images in the dataset were set to 224 × 224 pixels. This picture size is used by a lot of deep learning models.

Image quality is resolved in the third step of decomposition. It eliminates background noise and restores the original picture's crucial details. A tiny amount of data contains the majority of the info in many photographs, while the rest is unimportant. Images in the original dataset have varying degrees of quality. to see how changing the unique value impacts the picture. to chose the single value [illegible]9 to procedure the photos in data set.

3.3. Classification using ACNN-BLSTM Model

It is then subjected to the ACNN-BLSTM [25] model for efficient disease identification in crops. An innovative time network approach called ACNN-BLSTM can be created by integrating CNN, BLSTM network, and a lightweight Effective Channel Attention (ECA) component into a unified structure. This will improve feature extraction and prediction accuracy. The offered method makes full use of data to automatically learn and extract local and long memory characteristics from time series, hence reducing model difficulty. Furthermore, the attention process is now well-established for extracting additional crucial aspects.

Finally, the forecast jobs were executed using the dense technique, which has numerous fully connected (FC) layers. CNNs were used to effectively extract characteristics from the data in this scenario. Similar to the standard NN architecture, convolutional neural networks (CNNs) reduce the number of parameters in the connection layer by establishing local connections between neurones. In particular, it is a connection component of the CNN's n-1 and n layers. The BLSTM network, which applies as both a LSTM network to all learnt arrangements, was used to construct an even more accurate forecasting technique. The two LSTM networks share an output layer, allowing them to provide complete context data at every point in the sequence.

An enormous opportunity exists for deep convolutional neural networks (DCNNs) to become more efficient through the Channel Attention (CA) method. But, one of the offered ways is committed to building extra demanding components for obtaining optimum efficiency that unavoidably computational weight of method. The purpose of developing ECA, a lightweight and minimally difficult component, was to reduce calculation time and prevent method over-fitting. The ECA could figure out the association between the several channels and also assign weights to each one. The important characteristic has been given more weight in the time series data, whereas the unimportant feature has been given less weight [26]. Therefore, ECA focusses on relevant data that makes the network more sensitive to important traits. When it comes to channel Global Average Pooling (GAP), the ECA is in charge. After that, ECA captures the local connections using all of the channels, including their k neighbouring channels. Through the execution of rapid 1D convolution as

$\omega = \sigma(C1D_k(y))$ (1)

where C1D is the 1D k is the 1D convolutional kernel size. Rather than manually changing k, ECA uses a channel dimensional adaptably mapping method to find its value. The corresponding connection was shown to be because the 1D convolutional kernel size k is precisely proportional to C.:

$C = \phi(k) = 2^{(\gamma * k - b)}$ (2)

So, to deliver the C, the kernel extent k is adjustably distinct as:

$k = \psi(C) = \left|\frac{log_2(C)}{\gamma} + \frac{b}{\gamma}\right|_{odd}$ (3)

where $| |_{odd}$ implies the adjacent odd sum. Both c and b have their parameters set to [2, 1] in this case. Compared to the lowest dimensional channel, the high dimensional one has a noticeably shorter interface range when dealing with non-linear mapping. Lastly, crop diseases are identified from the input data using the softmax layer. The following part details how the suggested model is fine-tuned using a hybrid SA-GSO model.

3.4. Optimal Parameter Identification using SA-GSO

The initialiser and optimiser are crucial components of the model training pipeline that considerably affect the output of the final tests. During the routing phase, the SA-GSO [27] approach can be utilized efficiently to determine the optimal destination. Intelligently calibrated GSO relies on the glow-worm's light signaling to entice additional glow-worms. This strategy employs a randomly dispersed swarm of solution space glow-worms. A possible answer is shown by the placement of each glowworm. The most luminescent glow-worm will entice the least luminescent glow-worm. The global optimisation of the method is thus achieved. First, there are the essential steps.

Step 1. Setting the initial value of GSO's primary parameter. Here you can find the following parameters: upgrade rate b, population size g, fluorescein upgrade rate g, perception radius rs, move step s, threshold nt for the sum of the neighbourhood, and the decision field's group of glowworms, Ni(t).

Step 2. Using the subsequent equation, the fitness value of glow-worm adjusted according to the fluorescein value:

$l_i(t) = (1-\rho)l_i(t-1) + \gamma J(X(t))$ (4)

where r signifies the fluorescein enhancement constant, and denotes the fluorescein decompose constants, which range from zero to one.

Step 3. Glow worms always go for the brightest people within their radius. $r_d^i(t)$ for the way neighbor set $N_i(t)$.

Step 4. Compute the likelihood $p_{ij}(t)$ of glow-worm $X_i(t)$ disturbing the glow-worm $X_j(t)$ from their vibrant by Equation (5):

$$p_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_i(t)} l_k(t) - l_i(t)} \quad (5)$$

Step 5. Upgrade worm X(t) in Equation (6):

$$X_i(t+1) = X_i(t) + s \times \left[\frac{X_j(t) - X_i(t)}{\|X_j(t) - X_i(t)\|}\right] \quad (6)$$

Step 6. Upgrade the dynamic result radius $X(t)$ in Equation (7):

$$r_d^i(t+1) = min\{r_s, max\{0, \beta \times (n_t - |N_i(t)|)\}\} \quad (7)$$

Based on predetermined standards, the GSO algorithm will typically set the step size to a constant number. This study takes into account two elements that affect the step size—the number of rounds and the distance among the ideal glow-worm at the nith round—because choosing the right step size is vital for real outcome. The ith glow-worms must be quite distant from the ideal solutions for the step size to be large; otherwise, it is microscopic. Optimal stride size for the ith glow-worm is zero in the nith round. Before developing the SA-GSO algorithm, to examine the effects of varying the step size on the GSO algorithm. Afterwards, to apply the self-adaptive step size formulation, which is detailed later on:

$$s_i(t) = D_i(t).\left(len\left(e - \frac{t}{N_t}\right)\right)\|x_i(t) - x_b(t)\| \quad (8)$$

where each $x_i(t)$ is dispensed to exactly one $s_i(t)$, even if it could be allocated to two or more of them, where $D_i(t)$ arbitrary sum in unchanging distribution, N_t denotes maximum iterations, and $x_b(t)$ designates the location of the optimal glow-worm at the tth round.

Because the fitness with the highest value, fitness can be computed using the largest parameter assessment from [27]. The maximal fitness function can be evaluated subsequent formulas:

$$B = \frac{1}{3a^2 \eta}\sum_{K=1}^{a}[DT + RT + HT] \quad (9)$$

whereas B characterizes fitness function.

4. Results and Discussion

Recent advances in deep learning have led to the proposal and implementation of new optimisers and initialisers [28]. Hence, the model is fine-tuned to choose the right initialiser and optimiser before the trial. Using the TensorFlow-based Keras framework, which primarily modifies the epoch, besides batch limits, this experiment is executed on a GPU situation. Table 1 displays the experimental setup and parameters..

Table 1: Environmental Setup

Numerical Value	**Parameter**
Using the Keras outline based on Tensorflow.	Development environment -
0.0001	Learning Rate
CUDA 9.0 besides Tensorflow-GPU 9.0	GPU
8	Batch
Dropout is used to prevent classic overfitting with a limit of 0.5.	Dropout

Throughout the experiment, to make use of 58725 images from the dataset to have 4,540 images to work with as test samples and a set of training samples. Table 2 shows the data distribution for the training samples, which are split 8:2 between the training set besides verification set.

Table 2: Dataset Description

Dataset	**Effect**	**No. of images**
Train	Train the archetypal	35182
Val	Regulate the parameters in the exemplary	8795
Test	Test the accuracy of the classic	4540

4.1. Validation Analysis of proposed model

The presentation of the proposed perfect is associated with existing techniques in terms of different metrics is given in Table 3 besides Figure 2 to 3.

Table 3: Analysis of different models

Measures	**AE**	**CNN**	**BiLSTM**	**CNN+BiLSTM**	**Proposed model**
Accuracy	95.862	95.517	94.828	95.172	97.586
Sensitivity	93.103	94.483	92.414	92.414	97.241
Specificity	94.621	96.552	97.241	97.931	97.931
Precision	95.54	96.479	97.101	97.81	97.917
FPR	01.3793	03.4483	02.7586	02.069	02.069
FNR	06.8966	05.5172	07.5862	07.5862	02.7586
NPV	98.621	96.552	97.241	97.931	97.931
FDR	01.4599	03.5211	02.8986	02.1898	02.0833
F1-Score	95.745	95.47	94.7	95.035	97.578
MCC	91.864	91.054	89.76	90.483	95.175

Presentation metrics like accuracy, false positive rate (FPR), false discovery rate (FDR), F1-score, besides Matthews correlation coefficient (MCC) are examined for each model. The suggested model outperforms other models, including Autoencoder (AE) at 95.862%, CNN at 95.517%, BiLSTM at 94.828%, and CNN+BiLSTM at 95.172%, with the highest accuracy of 97.586%. The suggested model also outperforms the other models with a sensitivity of 97.241%, which indicates the model's capacity to accurately detect true positives. CNN+BiLSTM and the suggested model both attain the highest value of 97.931% for specificity, which quantifies the true negative rate. The suggested model's precision of 97.917%, which is marginally higher than that of other models, shows that it is dependable in predicting true positives. In terms of error rates, the suggested model exhibits low false positives and false negatives, with the lowest FPR at 2.069% and the lowest FNR at 2.7586%. With the highest F1-score of 97.578%, the exhibits balanced precision and recall, with NPV and FDR of 97.931% and 2.0833%, respectively. Lastly, the suggested model performs strongly overall, as evidenced by its 95.175 MCC, a balanced indicator of the model's quality that is noticeably higher than the other models. As demonstrated by these findings, the suggested model outperforms the others in a sum of metrics, most notably accuracy, sensitivity, and F1-score.

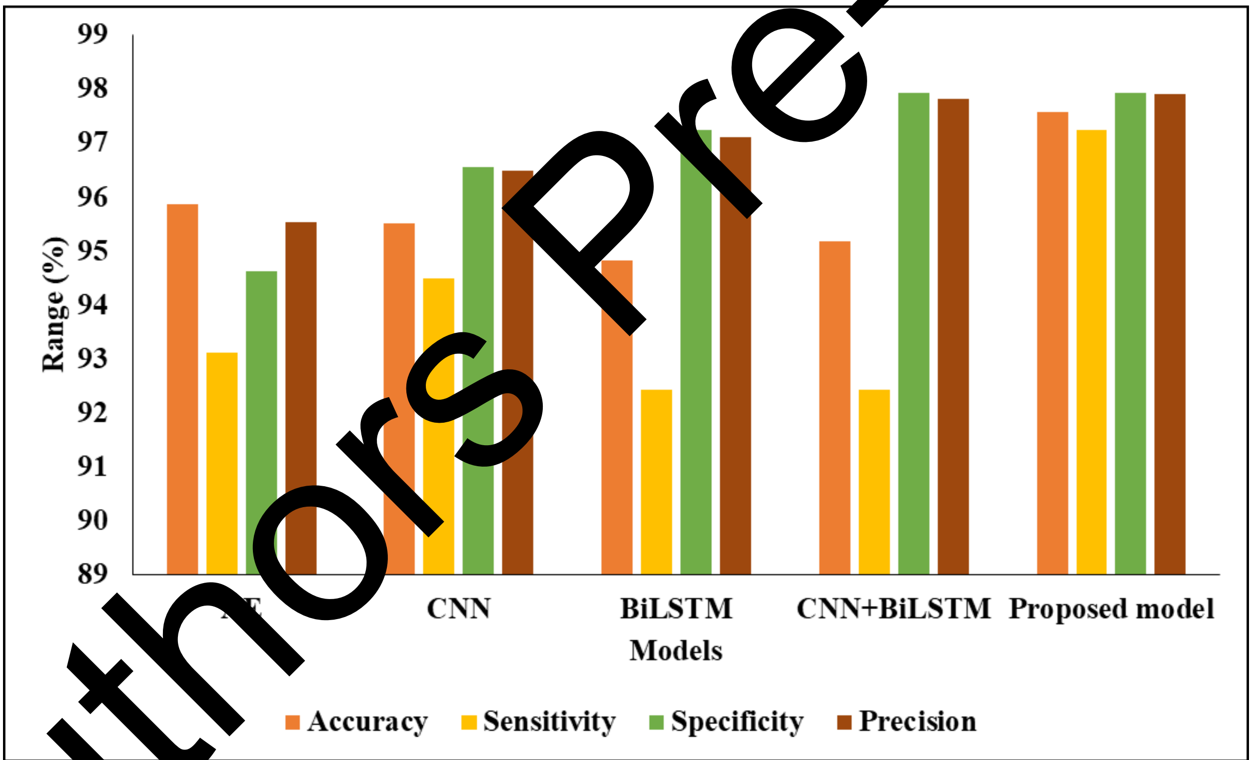

Figure 2: Graphical Explanation of proposed classical

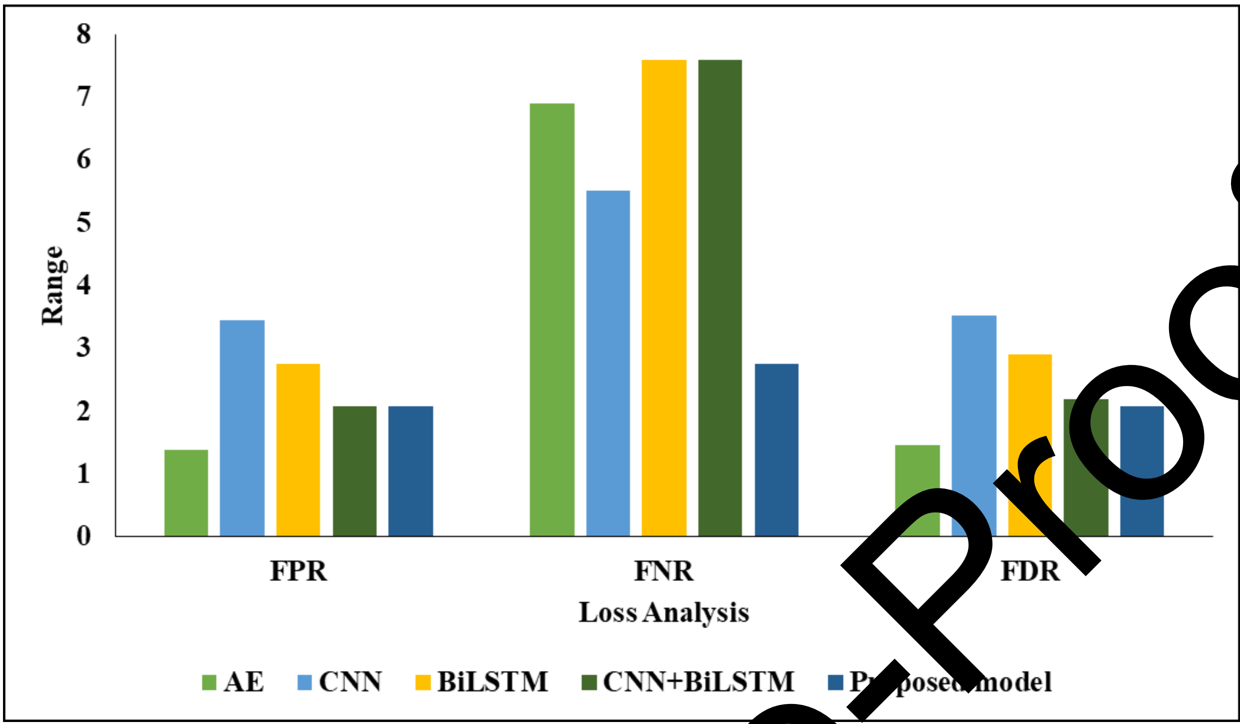

Figure 3: Loss Investigation of projected model

5. Conclusion

Our IoT system has proven to be useful in agriculture industry crop disease recognition systems. The suggested strategy may be automatically applied to many crop varieties thanks to the integration of IoT technology. In addition to identifying the condition, it distinguishes between different stages of the disease. This work proposes a new DL technique that uses integrated sensors to detect disease at an earlier stage. The suggested method makes use of a sum of sensors to collect data from the input source. Also, illness detection makes use of the ACNN-BLSTM model. The results are examined using multiple metrics after a battery of experimental analyses. The SA-GSO technique is employed to select the hyperparameters associated with the ACNN-BLSTM model in the most optimal manner. The outcomes show that the suggested method is superior on several fronts. Future research can focus on determining reasons why some circumstances. Improving precision at the low end boosts the efficiency of the scheme. In situations when image quality is an issue, to calculate standards and criteria for the images included in the dataset. One such approach may be the usage of charts comprised in the photos. Next, the image's colours may need to be adjusted to meet standards as part of the preprocessing. Afterwards, visual care systems and target detection can enhance image data.

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