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Auxiliary Deep Dense Network (ADDN) Based Plant Growth Estimation

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Abstract:

Accurate phenotyping is essential to plant breeding and understanding the impact of the environment on plant growth and yield. Early detection and accurate diagnosis are essential to manage and prevent plant stress effectively. Single-plant growth monitoring aids precision agricultural decision-making to reduce the costs related to pesticides, fertilizers, and labor. Accurate and rapid plant disease detection is critical for enhancing long-term agricultural yield. Disease infection poses the most significant challenge in crop production, potentially leading to economic losses. Over the last 15 years, significant advances in detection, monitoring, and management of plant diseases have been made, largely propelled by cutting-edge technologies. Deep Learning enabled the development of novel cropping systems, allowing for targeted management of crops, contrasting with traditional, homogeneous treatment of large crop areas.

This technique uses the concept of global relative optimality from fast efficient deep learning to solve the limits of conventional algorithms that focus on extracting absolute features and thereby improve accuracy in plant growth.

Keywords: *Plant Growth Estimation; Auxiliary Deep Dense Network (ADDN); Deep Learning; Plant Phenotyping; Image Segmentation; Gabor Filter; Feature Extraction; Leaf Area Index (LAI); Biomass Estimation; Precision Agriculture.*

1. Introduction

Plant infections significantly impact both crop quality and quantity. Early prediction and recognition of these infections are vital to prevent crop damage and enhance yield. In India, agriculture only contributes around 17% to the country's GDP [1]. India ranks top in critical crops like tomatoes, potatoes, and pepper [2]-[4]

Plant phenotyping involves measuring and studying plant features (i.e., phenotypic traits) such as growth, development, and responses to environmental stimuli and pathogens [5]. Accurate phenotyping is essential to plant breeding and understanding the impact of the environment on plant growth and yield [6]. Agriculture consumes about 70–90% of the world's water resources [7]. The availability of water for crops and their resistance to shortages during growth affect the overall yield, quality, and profitability of field produce. With global climate change and the growing imbalance between water supply and demand, farmers are dealing with increasing shortages in agricultural water resources [8]. Therefore, it is important to develop tools to monitor crop water status on a large scale and at low cost [9].

In the current era characterized by significant technological advancements, it is noteworthy that farmers continue to follow traditional practices regarding disease identification in crops. Rather than depend on modern specialized tools, farmers persist in personally and visually examining the crops to detect any signs of disease [10]. The traditional methods of visually inspecting and evaluating crops solely based on the farmer's expertise present several challenges and limitations in agricultural research.

Early detection and accurate diagnosis are essential to manage and prevent plant stress effectively [11]. Advances in both artificial intelligence (AI) and imaging sensor technologies have shown potential for the accurate identification and prediction of plant stress symptoms [12]. Combining AI and thermal camera has the potential to mitigate the use of pesticides, enhance crop productivity, and bolster worldwide food security by enabling the identification and precise diagnosis of plant stress symptoms [13].

The diagnosis of infected leaf disease while asymptomatic or with early-stage symptoms is challenging for plant producers. This is particularly the case with large volumes of stock where close visual inspection is unlikely to be practical or cost-effective and may be biased or inaccurate. Diagnosis can be confirmed by examining spores under the microscope or using DNA-based diagnostic assays that can detect the fungus, even in symptomless tissue [14]-[18]. However, while these methods are easy to apply when sampling is guided by visual detection of symptoms, a random sampling from asymptomatic plants would likely be ineffective and expensive. Thermal imagery provides a promising method of pre-visual and early disease detection that could be spatially scaled for rapid screening. Physiological responses in plants subject to infection by pathogens often include changes in chlorophyll and other pigments, leaf water content, and key photosynthetic variables such as stomatal conductance, transpiration and photosynthesis that may be detected by shifts in leaf temperature and changes in indices or plant functional traits [19]. Pre-visual or early detection of a range of diseases, in agricultural and forestry crops, have been demonstrated using thermal imagery at the plant level, often at broad scales [20]-[25].

Plant growth tracking is a complex and challenging task due to rapid dynamic growth, occlusion of leaves and changes in angular orientation of leaves. Plants grow continuously at meristematic tissues through the emergence of new leaves and roots. During the vegetative development of the plant, leaves emerge from the shoot and undergo various development stages. Leaf characteristics like size, shape and count vary considerably for different plant species and even between accessions of the same plant. Photosynthesis process and plant biomass are dependent on these leaf traits. Therefore, tracking plant leaves at different development stages is complex and, hence, essential for plant growth estimation and tracking.

To address the challenges mentioned above that are prevalent in modern agricultural settings, computer-aided automated studies such as ML and DL can be instrumental in facilitating precise, rapid, and early identification of diseases.

In a nutshell, the significant contributions of the proposed work are enlisted in the following:
– A novel CNN-based model to count the number of plants leaves has been proposed which has been provided two inputs i.e., segmented output and the original image for better accuracy

2. Literature survey

Plant image analysis is a significant tool for plant phenotyping. Image analysis has been used to assess plant trails, forecast plant growth, and offer geographical information about images.

CNN [26]-[28] is a popular method that has been widely used in the field of plant disease detection [29]-[31]. The dataset used by the CNN models should be of good quality, and it has to be properly labeled. The performance of the CNN models greatly depends on the quality and amount of data used to train the model. A. Harshitha et.al.[32] proposed a Crop Growth Prediction method using Ensemble KNN-LR Model. This model uses effective feature selection techniques to transform the raw data into a dataset that is machine learning compatible in order to guarantee that KNN-LR model operates with a high degree of accuracy. B. Sagan et.al. [33] develope an end-to-end 3D CNN model for plot-scale soybean yield prediction using multitemporal UAV-based RGB images with approximately 30,000 sample plots. Three commonly used 2D CNN architectures (i.e., VGG, ResNet and DenseNet) were transformed into 3D variants to incorporate the temporal data as the third dimension. Additionally, multiple spatiotemporal resolutions were considered as data input and the CNN architectures were trained with different combinations of input shapes. Wang, Y et.al.[34] poposed conditional encoder–decoder generative adversarial neural network in which One model performs high-precision spatial attribute interpolation for urban green spaces, and the other predicts and evaluates the environmental conditions for plant growth within these areas. Deb. M.et.al. [35] developed a convolutional neural network-based leaf counting model called LC-Net. The original plant image and segmented leaf parts are fed as input because the segmented leaf part provides additional information to the proposed LC-Net. The well-known SegNet model has been utilised to obtain segmented leaf parts because it outperforms four other popular Convolutional Neural Network (CNN) models, namely DeepLab V3+, Fast FCN with Pyramid Scene Parsing (PSP), U-Net, and Refine Net. Lee, Cheng-Ju et.al.[36] study integrated visible/multi-spectral UAV imagery with two deep learning methods, object detection and semantic segmentation, to obtain a visualized map that could assist in precise field monitoring and management for broccoli cultivation. S. Kolhar et.al. [37] use a deep neural network-based multi-class semantic segmentation algorithm to track each plant leaf in the image sequence. The model could track partially occluded and tiny emerging leaves throughout image sequences. In the second phase, they determine plant phenotypes like leaf count, projected plant area, emergence time of leaves using segmented images obtained in the first stage. H. Mahendra et al.[38], present work deep learning models

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are applied to identify the crop fields (crop mapping) and classification of crops for the yield estimation. The combination of machine learning and observations from more advanced satellite images was used for agricultural land classifications in a more efficient manner and with lower costs and reduced time than traditional classification method. M. Katherine et.al. [39] Deep learning, a type of artificial intelligence, is an approach used to analyze image data and make predictions on unseen images that ultimately reduces the need for human input in computation

Plant phenotypes like leaf size, leaf count, plant height, and biomass provide a quantitative description of plant growth resulting from the interaction of its genotypes with the environment. Plant breeders, geneticists and researchers need to understand these complex dependencies for accurate growth tracking, achieving higher yields and selection of suitable genotypes for the given environmental conditions[40]

3. Methodology

In particular, we place a focus on the processes that make up the blocks: Batch normalisation (BN), dropout, and activation are the functions that are accessible to be used. With a mean of zero and a standard deviation of one, the batch normalisation function controls the output of the layer such that it is contained within a predetermined range. By acting as a regularisation mechanism, this contributes to the enhancement of the neural network's stability and the acceleration of the training process. During training, the Dropout operation acts as a regularisation for each mini-batch by blocking a few neurons. This mimics the behaviour of a bagged ensemble of multiple neural networks. The dropout value is a measure of the number of neurons that are inhibited, ranging from 0 to 100 percent of neurons in a single layer.

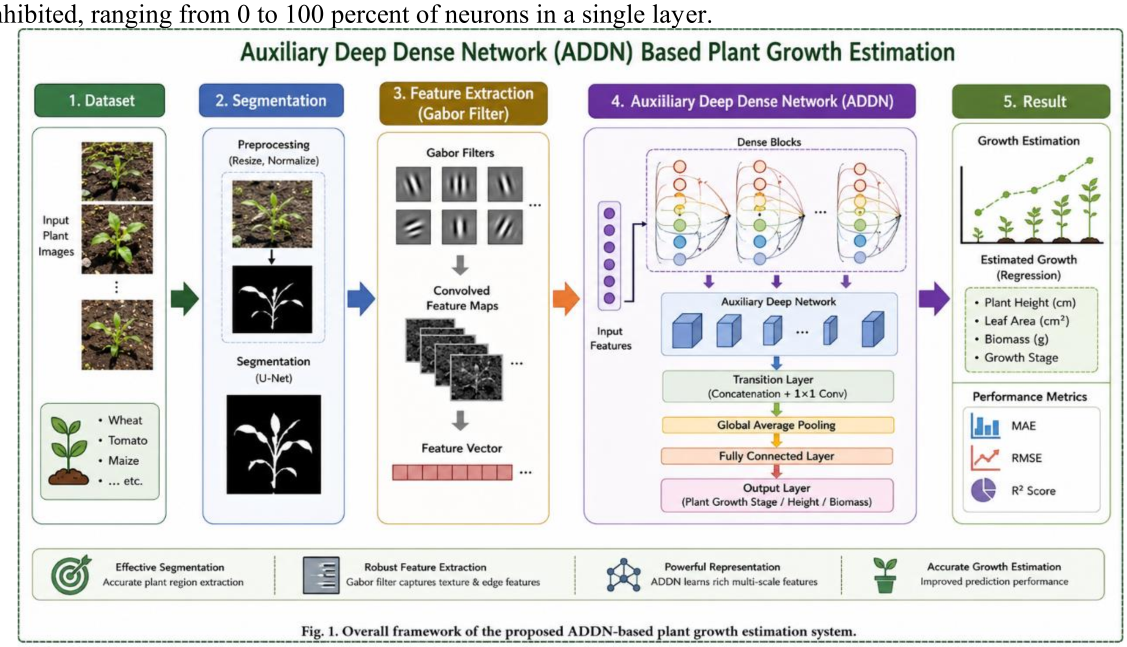

Fig. 1. Overall Architecture of the Proposed Auxiliary Deep Dense Network (ADDN)-Based Plant Growth Estimation Framework.

Segmented image is sent into the first layer as a vector is:

$$X = [x_1, x_2, \dots x_k] \quad (1)$$

K stands for the amplitude of the signal. Afterwards, data normalisation is done to reduce execution load. The mapping of data points between 0 and 1 is known as normalisation:

$$x = [\frac{x-min}{max-min}] \quad (2)$$

min and max are the lowest and highest values in the set of data, respectively. Before being sent into the convolution layer, this normalised data x is transformed into a 2D matrix using a reshaping procedure.
After covolution layer we got estimated the weight(w), bias (bj).

$x_i^{l,j} = \sigma[b_j + \sum_{a=1}^{m} w_a^j x_{i+a-1}^{l-1,j}]$ (3)

Activation function is indicated by the variable σ. Its nothing but ReLu,. ReLu function have higher efficiency and low execution time.

Max-Pooling Layer

By calculating the aggregation statistics of the nearby pixels, the Max-Pooling Layer maintains the scale invariant characteristic. They are useful for reducing dimensions in this way. There are two varieties of pooling: maximum and mean. The max-Pooling algorithm was used in our design. The max pooling layer avoids composite feature loss by finding the maximum response, or value, for each block. The max-pooling layer's final answer is:

$x_i^{l,j} = max_{n=1}^{r}(x_{(i-1)*T\ n}^{l-1,j})$ (4)

where n is pooling size and T is pooling stride.

Following equation models the Hidden layer to output .Proposed method have this capability

$h_t = g(W_{xh^{x}t} + W_{hh^{h}t-1} + b_h)$ (5)

$z_t = g(W_{hz^{h}t} + b_z)$ (6)

here, g indicates elementwise nonlinearity(it can be sigmoid or hyperbolic tangent), x_t is the input $h_t \in R^N$ is the hidden state having hidden units equals to N. Output is denoted by Z_t at instant t. pixel sequence $(x_{1,} x_2, \dots, x_T)$ having T number of coefficient, then h1 (letting $h_0 = 0$), z_1, h_2, z_2, ..., h_t, z_T.

4. Experimental Results

For plant detection, feature extraction was conducted using multiscale convolution layers in ADDN, which enabled the effective detection of leaves in images taken under different photographic conditions and resolutions. The detection of individual broccoli plants was processed using a feature extraction architecture of the ADDN -Like backend at the SSD frontend, where the input scale of the detector complies with the original SSD architecture. All the fine-tuned ADDN based deep learning models are optimized by the SGD algorithm. The learning rate for all the models was set to 0.001, and a batch size 32 was chosen. Dropout operation was added to all the pre-trained models on the ImageNet dataset to prevent over-fitting and improve the generalization of the models. The ADDN model is optimized by the SGD, a learning rate of 0.001 and batch size of 32 were used.

Figure 2 illustrates the sequential image processing and feature extraction pipeline used in the proposed Auxiliary Deep Dense Network (ADDN)-based plant growth estimation system. Figure 2(a) presents the original RGB input image of the tomato plant acquired under natural field conditions. Figure 2(b) shows the segmented plant region, where the leaf canopy is isolated from the background to retain only the relevant vegetation pixels. Figure 2(c) displays the thresholded binary mask generated during the segmentation process, highlighting the extracted plant structure for quantitative analysis. Finally, Figure 2(d) summarizes the extracted phenotypic features, including green pixel count, canopy cover coefficient (CCC), growth stage, above-ground biomass, plant area index (PAI), leaf area index (LAI), and color moment descriptors. These extracted features serve as the input to the proposed ADDN model, enabling accurate estimation of plant growth characteristics and developmental stages.

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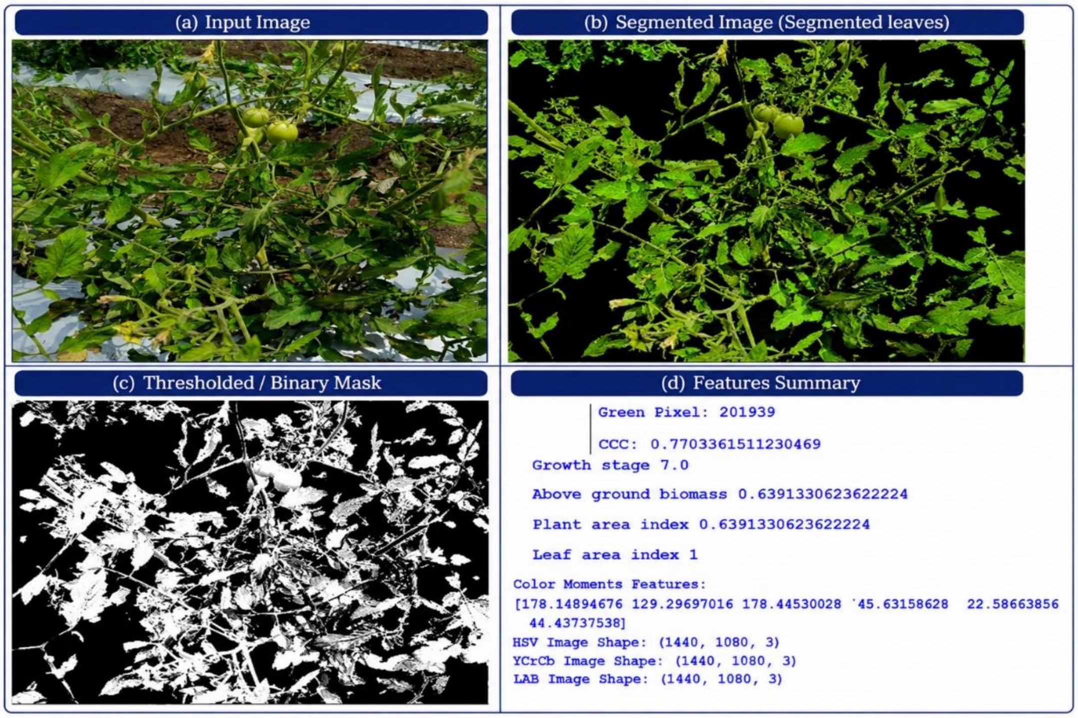

Fig. 2. Plant Image Processing and Feature Extraction Results for ADDN-Based Plant Growth Estimation.

By comparing the Proposed Network to other well-known approaches, we can confirm that the proposed method is resilient. The same dataset with the same folds is used to construct and evaluate all of these strategies. Below is a summary of the outcomes that were attained.

- True positive (TP): Total correctly recognized samples of current class
- True negative (TN): Total correctly recognized samples of remaining class
- False positive (FP):Total incorrectly recognized samples of current class
- True negative (TN): Total correctly recognized samples of remaining class

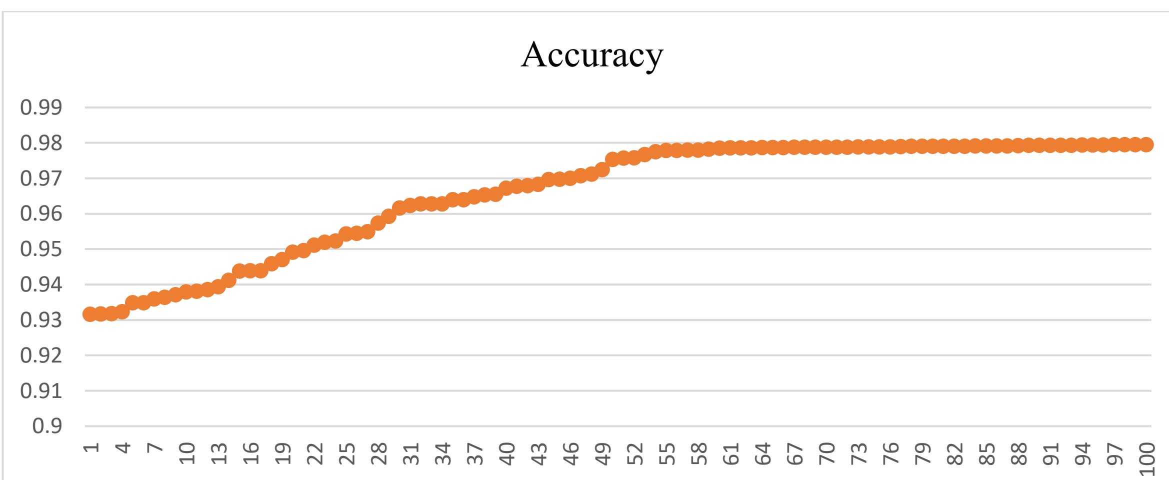

Fig 3 : Training Accuracy Vs epochs

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Accuracy

$$Accuracy = [TP + TN]/[P + N]$$

Fall-out or false positive rate (FPR)

$$FPR = [FP]/[N]$$

Specificity , selectivity or true negative rate (TNR)

$$TNR = [TN]/[N]$$

Sensitivity, recall, hit rate, or true positive rate (TPR)

$$TPR = [TP]/[P]$$

While existing CNN and DNN reach 92% and 91% accuracy, respectively, the proposed network achieves 95.30%. The accuracy of other methods, such as LSTM and SVM, is 92% and 91%, respectively.

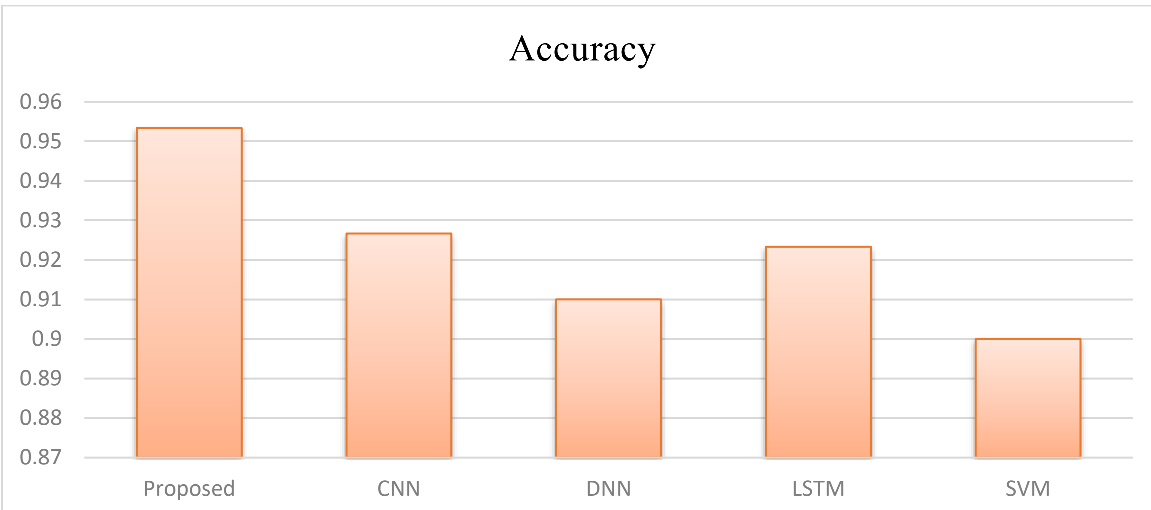

Fig 4 : Comparison of Accuracy

While existing CNNs and DNNs reach 98% and 97% sensitivity, respectively, the proposed network reaches 100%. Other methods, such LSTM and SVM, have sensitivity levels of 98% and 96%, respectively.

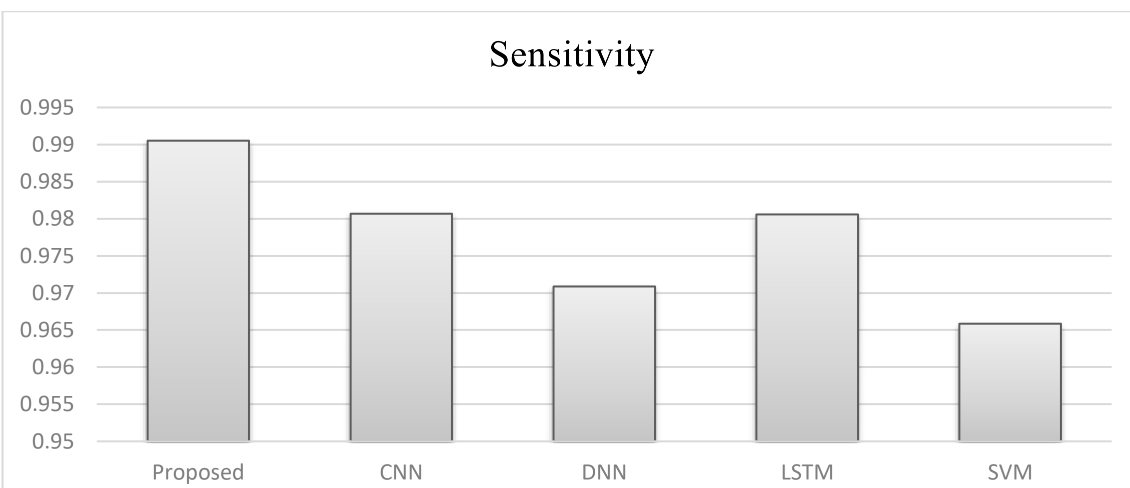

Fig 5: Comparison of Sensitivity

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In comparison to previous CNNs and DNNs, the proposed network attains a Specificity of 97%. Specificity is 94% for LSTM and 91% for SVM, two alternative methods.

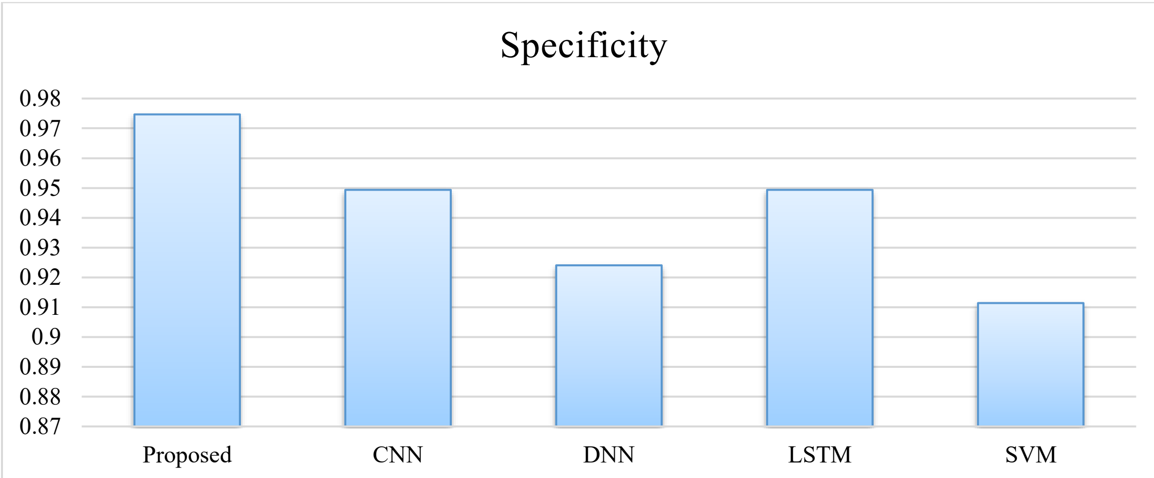

Fig 6: Comparison of Specificity

While competing CNNs and DNNs reach 91% and 90% specificity, the suggested network reaches 94%. Other methods, including SVM and LSTM, achieve a specificity of 89% and 91%, respectively.

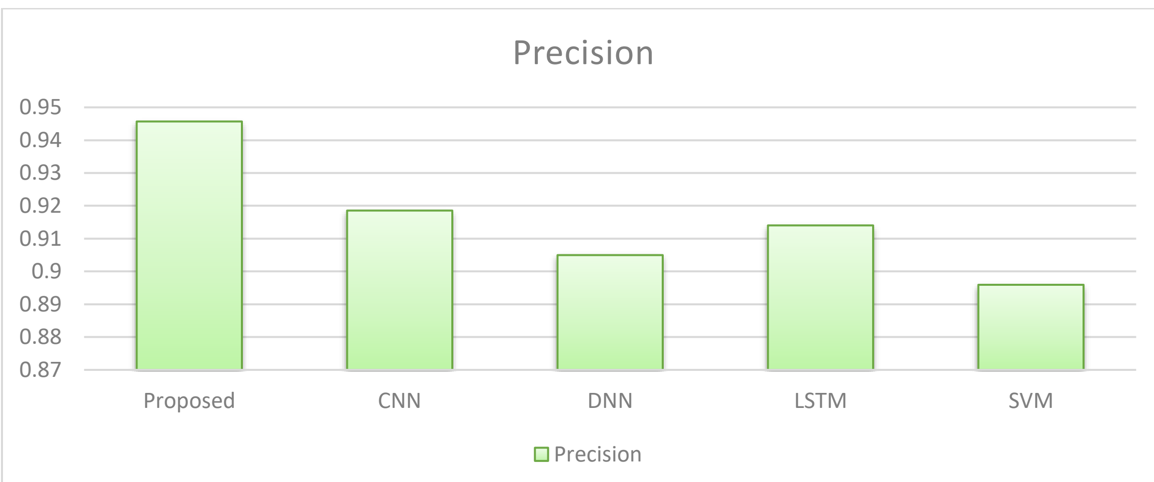

Fig 7 : Comparison of Precision

5. Conclusion

Plant growth tracking has potential applications in plant breeding research, crop management, understanding gene–environment interactions, stress analysis, and yield prediction. Plants are susceptible to a variety of diseases during their growth stages. One of the most difficult challenges in agriculture is the early diagnosis of plant diseases. If diseases are not detected early, they may have a negative impact on the overall output, resulting in lower revenues for farmers. This technique uses the concept of global relative optimality from fast efficient deep learning to solve the limits of conventional algorithms that focus on extracting absolute features and thereby improve accuracy in plant growth

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