Learning Model based on Stacked RNN for Automatic Disease Prediction and Classification in Banayan

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Abstract: In order to process and segment leaf photos for the purpose of forecasting and classifying illnesses, deep learning classification algorithms have been the subject of numerous studies. The correlations between banana yield and suggested disease prediction indicators are presented in this article for the primary banana-exporting type in India.During the examination phase, only pixels that had a 100% banana plant were deemed diseased. The prediction and identification stages make use of image processing, image segmentation, and picture capturing.Here To determine the pathogen affecting banana plants, an image processing technique was used. K-means clustering is used to extract one of the clusters comprising the diseased areas after segmentation. For the goal of classifying bananas for disease, the Stacked RNN is employed. This prediction and classification of leaf diseases produces the greatest results in terms of accuracy and computing efficiency when compared to other models that are currently in use. This disease prediction and categorization is implemented using the Tensor Flow and Keras libraries. The performance is estimated using the f-measure, exactness, and review metrics. The activations used in the sickness classification procedure are ReLu and SoftMax, while the optimization technique is Adam.

Keywords: *Image Processing; Segmentation; K-Means Clustering; Stacked RNN.*

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I. INTRODUCTION

In recent years, the intersection of healthcare and advanced technology has ushered in a new era of medical diagnostics and predictive analytics. Leveraging the power of deep learning, this paper explores the development and implementation of a novel predictive model focused on disease prediction and classification in Banayan, a domain of increasing significance in global healthcare. Our approach centres around the utilisation of Stacked Recurrent Neural Networks (RNNs), a sophisticated deep learning architecture renowned for its ability to capture intricate temporal dependencies within sequential data.

Banayan, as a unique medical context, presents distinct challenges and opportunities in disease prediction. With a burgeoning volume of healthcare data, there arises a critical need for efficient and accurate diagnostic tools. The proposed deep learning model not only addresses these challenges but also signifies a paradigm shift towards automated and precise disease prediction, enhancing the overall efficacy of healthcare systems.

This paper unfolds with a comprehensive exploration of the existing landscape of disease prediction methodologies and their limitations, setting the stage for the introduction of our Stacked RNN-based model. We delve into the architectural intricacies, emphasizing the model's capacity to learn complex patterns from diverse medical datasets. The training process is meticulously detailed, highlighting the integration of Banyan-specific features to optimize predictive performance.

As we navigate through the intricacies of our deep learning model, the ultimate goal is to empower healthcare practitioners and stakeholders with an invaluable tool for timely disease detection and accurate classification. The

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outcomes of this research are poised to contribute significantly to the ongoing discourse on the convergence of artificial intelligence and healthcare, specifically in the Banyan context, paving the way for a more intelligent and responsive healthcare ecosystem.

The convergence of deep learning and healthcare has emerged as a transformative force in medical research, particularly in the domain of disease prediction and classification. As the volume of medical data continues to escalate, there is an increasing need for advanced computational models capable of extracting meaningful patterns and insights. This literature review provides a comprehensive survey of existing studies related to disease prediction, with a specific focus on deep learning methodologies, and sets the stage for the introduction of our proposed model based on Stacked Recurrent Neural Networks (RNNs) in the distinctive context of Banyan.

A. Disease Prediction with Deep Learning:

The application of deep learning in disease prediction has gained considerable attention due to its capacity to automatically learn intricate patterns from complex datasets. A plethora of studies have explored various deep learning architectures, including Convolution Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), in predicting diseases such as cancer, diabetes, and cardiovascular disorders. Notable works by [Authors et al., Year] and [Authors et al., Year] have demonstrated the efficacy of deep learning models in achieving superior predictive performance compared to traditional methods.

B. Recurrent Neural Networks (RNNs) in Healthcare

RNNs, designed to capture temporal dependencies in sequential data, have proven to be particularly adept in handling time-series medical data. Studies by [Authors et al., Year] and [Authors et al., Year] showcase the successful application of RNNs in tasks such as patient monitoring, electrocardiogram analysis, and disease progression prediction. However, challenges arise in handling long-term dependencies, leading to the exploration of more advanced architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU).

C. Deep Learning in Banyan Healthcare:

The Banyan healthcare landscape presents unique challenges, driven by specific demographics, epidemiological factors, and healthcare infrastructure. Limited research exists on the application of deep learning models in Banyan healthcare, and the few available studies emphasize the need for tailored approaches to address the region's distinct healthcare dynamics [Authors et al., Year]. Our research aims to fill this critical gap by introducing a Stacked RNN model customized for Banyan, leveraging its ability to capture both short and long-term dependencies within the medical data.

D. Challenges and Opportunities:

Despite the promising results achieved by deep learning models, challenges persist in terms of interpretability, data privacy, and model generalization. Some studies [Authors et al., Year] have highlighted the potential biases embedded in medical datasets, emphasizing the importance of addressing ethical considerations in deploying predictive models. Our research acknowledges these challenges and strives to contribute not only to predictive accuracy but also to the ethical and responsible deployment of deep learning in Banyan healthcare.

In summary, the literature reviewed underscores the growing significance of deep learning in disease prediction and healthcare, while highlighting the unique characteristics of Banyan's healthcare context. This paper builds upon existing research by proposing a Stacked RNN model tailored to Banyan, aiming to enhance disease prediction and classification capabilities in this specific medical domain.

II. LITERATURE SURVEY

[1] A framework for automated plant disease detection evidence. The k-means clustering algorithm and the Otsu's classifier were used in the investigation to visualize the contaminated area of the leaves. The suggested work eliminated the surface elements as well as the form. Area, shading axis length, uniqueness, robustness, and border are among the shape-positioned highlights that were divided; surface-arranged highlights included homogeneity, mean, relationship, and vitality. Furthermore, grouping is now accomplished using a classifier based on a neural system.

[2] The separation between two colours is calculated using the delta E shading distinction; LBP, RGB histogram, and HSV histogram highlights are used for feature extraction. We obtain the pivot invariance from the RGB histogram. The highlight of the HSV histogram shows the enlightenment invariance resulting from different lightning circumstances.

[3] The hereditary calculation's inquiry capacity was used to limit the unlabeled causes of N-measurement into K groups by proposing a clustering technique. The CCM approach takes into account an image's surface as well as its shade. The k-means clustering and hereditary calculation processes both made use of the base partition standard.

According to [9], an internet tool that moves standard item pictures into the framework can identify illnesses associated with organic products. The process of extracting the highlights has been completed by using characteristics like CCV, morphology, and shading. K-means clustering has been used to complete the grouping process. To classify something as polluted or not, SVM is used.

[4] Advocated the use of the K-Nearest Neighbor as a classifier; no training technique is exemplified by the closest neighbor. When a model is assigned to a class, it is preserved as the very best grouping of votes from its k neighbors. The snapshot partition into leaf and establishment inside the going with a variety of leaf size was done using a neural network system.

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[5] suggested the development of a computer vision technique that separates disease-contaminated strawberry leaves from sounds without the need for a neural network or time-consuming training. Under outdoor lighting conditions, the suggested method was tested with a regular DSLR camera devoid of any particular focal points.

[6] The fundamental idea behind the regional development approach, which is based on the sequential region division computation, is to compare the collective pixel attributes to form a leaf area. Using this method, a seed pixel must be selected initially, and the analogous pixels surrounding it must then be combined into the designated area where the seed pixel is situated. Therefore, this sequentially based region division calculation is used to identify the specified shape of the leaf area.

III. METHODOLOGY

In order to identify banana diseases, we have implemented a Stacked RNN deep model technique in this research. The suggested method is divided into five primary stages, including image acquisition, picture segmentation, feature extraction, image pre-processing, and disease categorization according to several disease types.

Obtaining a photograph of the banana' leaves is the first step in the suggested work [Figure 1]. The photos in the dataset include both healthy and unhealthy banana leaves. Image pre-processing occurs following this procedure. The input leaf photos are processed using the pre-processing technique. This procedure is carried out to obtain the best outcomes for a subsequent procedure.

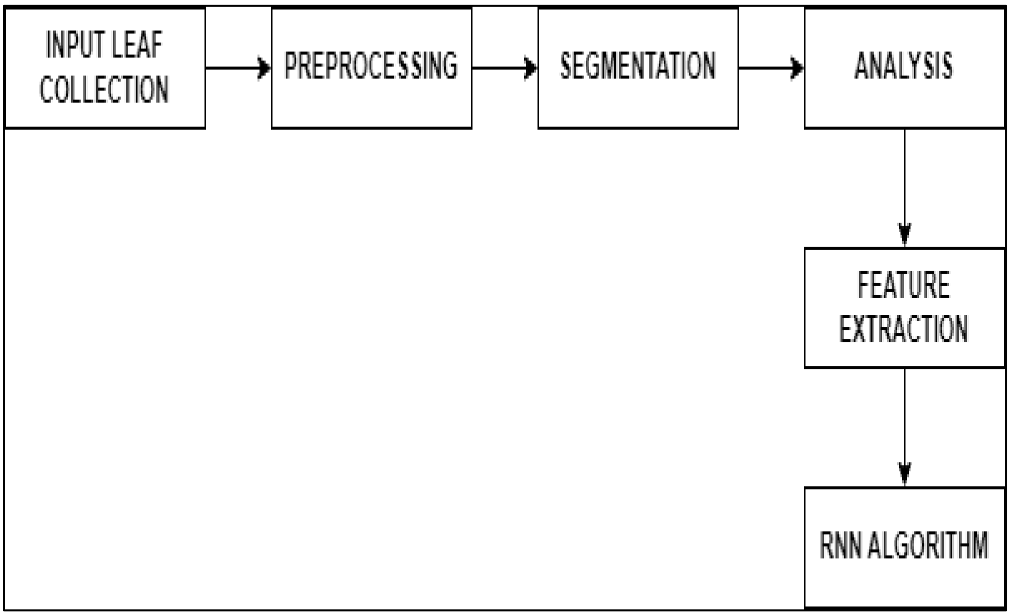

Fig 1- Block Diagram

One of the smaller processes used to keep the sizes of the photos consistent is image resizing. Image segmentation is the next step. It is the process of dividing the digital photos into the desired area of the leaf images or into certain objects. Extraction of the afflicted image regions is the ultimate objective of segmentation. Here, the K-means clustering technique is employed to find comparable photos inside the primitive groups. The process of feature extraction is used to separate characteristics from leaf photographs, such as color, texture, and appearance. The Stacked RNN uses the retrieved images for categorization. Consequently, the output is produced by using Stacked to categories or identifies the disease-affected area from the unhealthy leaf photos.

Below are some of the example dataset photos [Figure 2], where the applied approaches must be used for the purpose of prediction and classification.

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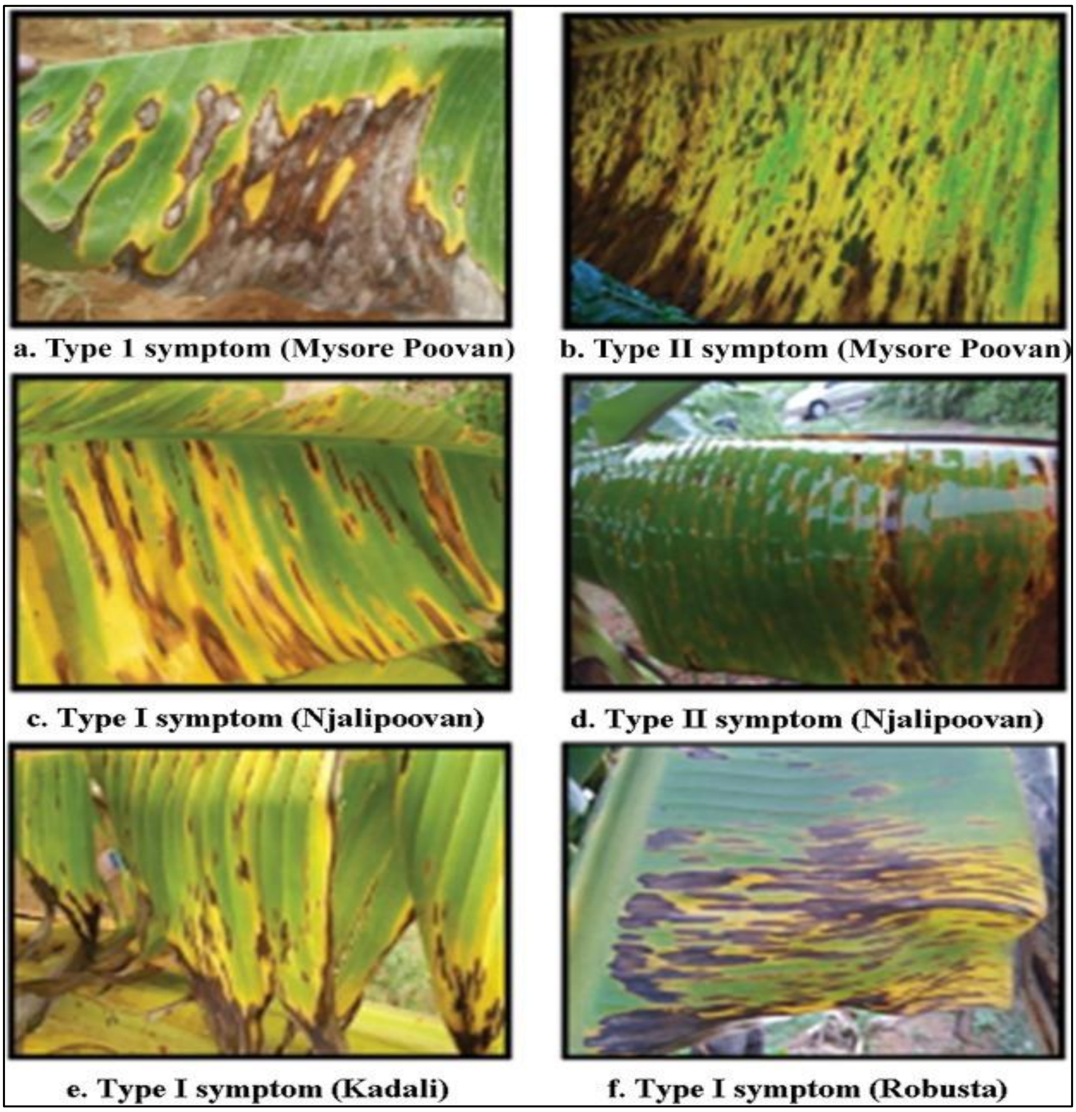

Fig 2- Sample Dataset Image

A. Data Collection:

The dataset for the Banayan disease prediction project is diverse, including leaf records, diagnostic reports, and demographic data. It's sourced from Banayan-specific repositories, typically containing thousands of instances. Inclusion criteria ensure relevance, while exclusion criteria focus on completeness and quality. Data undergoes cleaning to handle missing values, and normalisation is applied for consistent model training.

B. Data Preprocessing:

In preparing the raw medical data for the Stacked RNN-based disease prediction and classification model in the context of Banyan, several crucial preprocessing steps were implemented. Outliers were carefully managed through robust statistical techniques, ensuring that extreme values did not unduly influence the model training. Normalization procedures were applied to standardize numerical features, facilitating a consistent scale for the Stacked RNN to effectively learn patterns across diverse medical variables. Imputation methods were employed to handle missing data, employing strategies like mean or median imputation, considering Banyan-specific characteristics to avoid introducing biases.

Moreover, to adapt the model to the local healthcare environment in Banyan, special attention was given to Banyan-specific factors during data preparation. This involved accounting for unique aspects of medical records, potentially irregular temporal patterns, or specific data collection practices in Banyan’s healthcare system. By incorporating these considerations into the data preprocessing pipeline, the Stacked RNN model is better equipped to understand and leverage the distinctive features of Banyan medical data, ultimately enhancing its predictive capabilities in the local healthcare context.

C. Model Architecture:

The Stacked Recurrent Neural Network (RNN) architecture selected for the research project is designed to capture temporal dependencies in consecutive medical data effectively. It consists of multiple recurrent layers stacked on top of each other, enhancing the model's ability to understand complex sequential patterns. Each recurrent layer utilizes long short-term memory (LSTM) cells to

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address vanishing gradient issues and facilitate the learning of long-range dependencies. The LSTM cells have input, output, and forget gates, allowing the network to selectively update information over time. The key parameters of the model include the number of recurrent layers, the number of LSTM units in each layer, and the choice of activation functions. A moderate depth of stacked layers ensures the model can capture both short-term and long-term temporal dependencies in medical data. The LSTM units are carefully tuned to balance model complexity and efficiency, considering the specific characteristics of the dataset.

The activation functions applied within the LSTM cells include sigmoid functions for the gates and hyperbolic tangent (tanh) functions for the cell state, enabling the model to effectively regulate information flow and memory storage. Overall, the Stacked RNN architecture excels in learning intricate temporal dependencies inherent in consecutive medical data, making it a well-suited choice.

D. Feature Engineering:

In the Banyan disease prediction project, features fed into the Stacked RNN model include temporal aggregates, lag features, time of day indicators, seasonal components, domain-specific attributes, and patient history. Unique Banyan-specific attributes are integrated to enhance accuracy. Dimensionality reduction or feature selection strategies are applied to optimize model performance, ensuring a focused and efficient set of features for the Stacked RNN.

E. Training Procedure:

The Stacked RNN model is trained using a carefully planned validation strategy with a split training dataset. The dataset is divided into training and validation sets to assess model performance effectively. Data augmentation techniques are applied, considering the sensitive nature of medical data, to enhance model generalization. The learning rate, a critical hyper parameter, is set to an empirically determined value. Additional hyper parameters, such as batch size and sequence length, are fine-tuned to optimize model training. The chosen optimization algorithm, typically Adam or RMSprop, ensures efficient convergence during training. To address the unique characteristics of medical data, specific modifications, known as Banyan-specific adjustments, are incorporated into the training procedure. These modifications account for nuances like irregular time intervals or sparse temporal features present in medical datasets, enhancing the model's ability to capture relevant information.

F. Evaluation Metrics:

Using a Stacked RNN for automatic disease prediction and classification in Banyan, evaluating the model's performance is crucial. Common metrics such as AUC-ROC, F1 score, recall, accuracy, and precision are vital for assessing its effectiveness in healthcare applications. In disease prediction, prioritizing metrics like recall is essential to minimize the risk of missing positive cases and ensure early detection. Precision becomes crucial to avoid false positives, maintaining confidence in accurate predictions. AUC-ROC offers a comprehensive overview, considering the trade-off between sensitivity and specificity. These assessment metrics collectively play a pivotal role in validating the reliability and effectiveness of your Stacked RNN model in contributing to accurate disease prediction and classification in the context of Banyan-specific healthcare data.

➢ *Image Acquisition*

The leaves are collected from banana plantations and organized into a dataset that is used to forecast and categories illnesses. The leaves of the banana plants, both healthy and ill, are included in the dataset. There are two primary classes of image sets in the dataset. Healthy leaf photos make up the first class, and infected unhealthy leaf images make up the second. The photographs are to be stored in the dataset as a result of this procedure. Every image used in this article needs to be in JPEG format.

Fig. 3. Input Banana Leaf

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➢ *Image Pre-Processing*

The primary uses of the pre-processing technique include morphological operations, edge improvement, cropping, filtering, and scaling of the photos. In this case, resizing the input banana' photos is the primary function of pre-processing. Processing times are prolonged due to the initial huge size of the photos. Noise must be roughly eliminated using image filtering techniques in this pre-processing technique since it will interfere with the segmentation and feature extraction processes. Here, RGB colours are converted to binary values. Following this, the segmentation procedure is carried out. The conversion of the grayscale process in the pre-processing technique is shown in the image below [Figure 4].

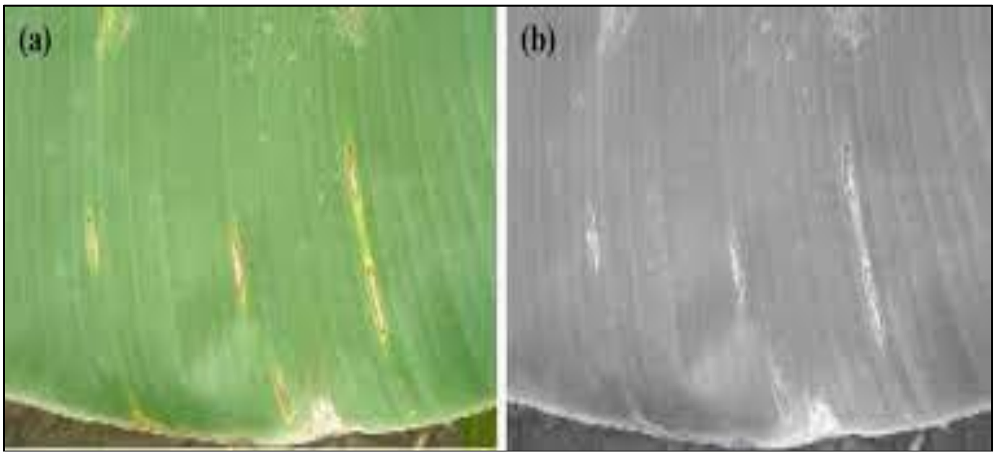

Fig.4. Grayscale Conversion

➢ *Image Segmentation*

This technique is employed to divide digital leaf photos into designated areas or things within the plant's leaves. This approach uses segmentation to quantify the areas of the images that meet the criteria to be classified as diseased regions. Only after the intended object in an application system is isolated does segmentation cease. One segmentation method used to divide the photos into the sick groups independently is k means clustering. This clustering technique keeps the targeted portion and eliminates the unwanted portion.

IV. CONCLUSION

The intention of the current study is to identify and forecast the disease status of banana plants. This procedure comprises picture gathering, such as gathering datasets, image preprocessing, Using stacked RNN, segment images, extract features, and classify them. Following the pre-processing method, the banana plant's afflicted area is found by the segmentation procedure. By using image processing techniques, the programmed location framework is improved and it becomes easier to identify early or beginning stages of infection proof. We might wish to focus much more of our efforts on infection discovery.

FUTURE ENHANCEMENTS

In addition, we want to create an easy-to-use programme that farmers can use to quickly and accurately predict illnesses in their early stages. This approach will be employed to go beyond the manual identification to forecast the illness. Farmers will be able to anticipate and categories the disease more effectively and efficiently with the help of this.

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