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FUSION OF DEEP LEARNING TECHNIQUES WITH TIME SERIES ANALYSIS FOR CROP YIELD PREDICTION FROM SATELLITE REMOTE SENSING DATA

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ABSTRACT

Artificial intelligence (AI) technology, such as computer vision methods and Deep learning algorithms, have become potent instruments for transforming agricultural practices. Artificial Intelligence (AI) facilitates real-time monitoring of crop growth, health, & yield prediction by evaluating data from multiple sources, including weather sensors, satellite imaging, and IoT devices. The potential of AI-based systems to improve crop management techniques through precision agriculture—which involves focused pest control, irrigation, & fertilizer application—is highlighted in this abstract. To fully realize the advantages of AI in crop monitoring, however, issues like data privacy & model interpretability need to be resolved. In general, the incorporation of AI technology has auspicious prospects for augmenting agricultural output, sustainability, and adaptability to fluctuating environmental and financial constraints. Satellite remote sensing, combined with deep learning, can estimate the crop yield quite accurately. In this paper, we discuss the use of deep learning techniques with time series analysis to estimate crop yield from remote sensing technology. We explore how to combine convolutional neural networks (CNN) and recurrent neural networks (RNN) with traditional time series analytical techniques to exploit spatial patterns found in satellite images and historical crop production data. Experiments conducted on practical agricultural datasets demonstrate the utility of the proposed framework and highlight its potential for accurate and timely crop production forecasting.

Keywords: Deep Learning, Time Series Analysis, Satellite Remote Sensing, Crop Yield Prediction, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN)

1. INTRODUCTION

The yield of grain used in agriculture has been significantly reduced & will continue to be so due to rising average air temperatures and unusual harsh weather occurrences (Breshears et al., 2021). Industry 4.0's key ideas find their perfect implementation in smart agriculture. The processes involved in agriculture and food production have been put in jeopardy by climate change and global warming. These circumstances are becoming more and more crucial to regulate in order to prevent potentially catastrophic losses in crop cultivation. Water scarcity jeopardizes the food production chain, particularly in certain parts of the world. The problems posed by climate change therefore require a new strategy called as "smart agriculture," which combines conventional agriculture with artificial intelligence (AI) and autonomous technology (Cartolano Andrea et.al. (2024).

Agriculture is an important part of our country's economy which contributes to about 16 to 17% of the GDP and about 60 to 70% of our country's population is fed by agriculture. At the rate at which our country's population is growing, by 2050 we will need almost double the yield while we can increase the cultivable land by only 4% at most

(FAO 2018). However, it is anticipated that the world's population will continue to rise through the middle of this century, which would raise the need for food produced by agriculture. Over half of the calories consumed worldwide that are not meat come from maize, one of the main food crops grown worldwide (Zhang et al., 2019). To meet the development objectives of our country, we need to build nutritious, sustainable and inclusive food systems. In this way, by enriching agriculture, we can also eliminate extreme poverty. Using satellites or aircraft to collect data on crop growth, health, & yield over vast agricultural regions is known as remote sensing of agricultural crops. Farmers, agronomists, and legislators can use this method to gain insightful information that will help them make well-informed decisions on crop management techniques, resource allocation, & food security.

The first step in the procedure is the collection of satellite images, which picks up different spectral bands that correspond to distinct agricultural landscape elements. After that, specific software is used to process these photos in order to retrieve pertinent data including land surface temperature, moisture content along with vegetation indexes. Based on the quantity of chlorophyll & photosynthetic activity, vegetation indices, such as the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI), are frequently used to evaluate the health and vigor of crops. Low NDVI levels may be a sign of stress or slower growth, whereas high values show robust, actively developing vegetation. Warmer temperatures may be a sign of heat stress or water scarcity, hence data on land surface temperature can shed light on environmental factors and crop water stress. In a similar vein, maps of moisture content created using remote sensing data facilitate effective water management by monitoring soil moisture levels & irrigation needs.

Furthermore, crop mapping & classification using remote sensing techniques can help distinguish and map various crop varieties within agricultural fields. After optimizing a UAV platform to capture multispectral photos, Hassan et al. discovered a strong association between wheat biomass and the normalized difference vegetation index (NDVI), with the greatest R2 being 0.40 (Hassan et al., 2019). This data is useful for tracking crop rotation trends, calculating acreage, and evaluating potential yield. In order to automate data processing and raise the precision of crop monitoring forecasts, machine learning (ML) & artificial intelligence (AI) algorithms are being included into remote sensing workflows more and more. Early identification of pests, illnesses, and other crop health issues is made possible by machine learning (ML) algorithms that can learn from past data to identify patterns and anomalies in satellite imagery.

Moreover, crop yields can be predicted by AI- powered deep learning models using a mix of weather forecasts, yield data from the past, and data from remote sensing. By reducing production risks, scheduling harvests, and optimizing resource use, these models assist farmers in raising output and profit margins. In general, precision agriculture is made possible by the effective and sustainable management of agricultural resources, as well as the assurance of food security & environmental stewardship, through the use of remote sensing techniques for agricultural crop monitoring in conjunction with machine learning and artificial intelligence.

This paper is aimed at explaining how the use of DL has become revolutionary in agriculture, improving several practices in farming. DL is essential for monitoring plants' health and estimating yields through the analysis of big-scale agricultural data such as satellite imagery and sensors data. The DL algorithms can also assess crop status, growth, yield, and even give insights to allowing farmers to detect stress factors, diseases, and many other things so as to get proactive for the further increase of productivity. In this paper we using deep learning artificial neural networks, Sentinel-2 satellite footage has used to capture yellow rust of wheat in Roopnagar District, Punjab.

2. SCOPE OF THE STUDY

This proposed research work is based on agricultural data identification and provide better accuracy for measurement crops growth and production. The scope of study is based on different research work already done in the crops identification using satellite images along with remote sensing technologies & our research is based on Rupnagar District, Punjab.

3. METHODOLOGY

In order to forecast diseases and data on agricultural crop yield output, this research uses primary and secondary data analysis along with soft computing. The following are significant steps in this research:

3.1. DOWNLOAD SENTINEL-2A SATELLITE DATA

For this, download data from Sentinel-2A satellite according to the time of your crop day.

3.2. PRE-PROCESSING OF DATA: SUBSAMPLE AND AREA OF INTEREST FROM SATELLITE IMAGERY

Always change the resolution of the satellite image so that it becomes comparable to other commonly used imagery to match the scale of the imagery spectral band. Cut out the specific Area of Interest (AOI) from the larger satellite image. This helps to limit the view to the specific agricultural areas under consideration and hence reduces the computational time for the same.

3.2.1. REMOTE SENSING

Remote sensing is the process of collecting data about an object or a phenomenon on the earth's surface from a distance without coming in close contact with the object (Jong et al., 2004).

Figure 1. Remote sensing process (Research Made with the help of Google Image)

By detecting radiation emitted or reflected from objects or places, remote sensing is an essential tool for collecting data about the Earth's surface and atmosphere. This technique uses sensors on drones, planes, and satellites to gather data about the target's physical, chemical, biological, and geological characteristics. Sensors are installed on platforms (satellite, aerial, unmanned airborne devices) above the Earth's surface. Some are placed a few hundred meters away, while others are circling hundreds or thousands of kilometres above the surface. Sensors range from high-resolution imagers to radar systems. There are two types of remote sensing data collection: passive and active. When using active sensors, like radar, energy is directed at the target and the reflected signal is measured, whereas passive sensors, like spectral imaging, detect natural radiation from objects (Verma Samiksha et.al. 2024).

The information about a very faraway place can be obtained by using passive or active sensors to measure reflected or self-radiation from a specified distance. Passive sensors detect electromagnetic radiation from natural sources such as radiation emitted from the sun. Examples of passive sensors are aerial photography and optical satellites. Active sensors have their own source of radiation, examples are radio detection and ranging ((RADAR) and light detection and ranging (LIDAR). Remote sensing data can be collected using non-imaging and imaging methods. Non-imaging methods use ground-based sensors such as spectroradiometers while imaging methods use airborne satellite platforms observing the earth. Images captured by satellites or airborne instruments are collected at different resolutions as described in Table 2.

Aerial images are obtained from helicopters, aircraft, Unmanned Aerial Vehicles (UAVs) also called drones & balloons. Satellite images, captured by earth-orbiting satellites, are classified into several types: colour images, infrared images, multispectral images with 7-12 bands, and hyperspectral images with 50 or more bands (Y. Ma et al., 2015).

Either active or passive sensing techniques can be used for remote sensing. Passive sensing encompasses measurement of naturally occurring events. For example, sensors such as satellite- mounted charge coupled device (CCD) cameras can capture sunlight. Active sensing on the other hand is characterized by an internal sensor that transmits a signal to acquire data. This type of sensor typically includes a transmitter that sends out a specific signal, such as a particular light wavelength or electrons, which then bounce off the target. The sensor collects data based on the reflected signals. "Radar & LiDAR" are examples of active sensing technologies. There are two types of remote sensing technology, dynamic & passive remote detecting. Multi transient and multispectral distant detecting symbolism has been widely used for crop identification in past years since time arrangement of satellite pictures are accepted to be a financially savvy information source to survey land cover, for example, agricultural crops over huge regions in May 2017 (Liakos et al.,2018).

- Poor results may arise from crop detection based solely on individual pixel response analysis, neglecting to take nearby pixels into account.
- Accurately documenting crop location and paddock rotation history is becoming a crucial component of managing crops and ensuring the quality of the final output.
- ML and DL based algorithms will perform analysis on agricultural data using satellite images for getting high accuracy of crops identification.

Using satellite photography, crop detection, growth, and identity monitoring are increasingly regarded as attainable objectives.

Table 2 Different Types of Resolution

Resolution Type	Description
Spectral Resoluti	Certain wavelength periods that a sensor can
Spatial Resolution	Area that each pixel represents
Radiomet ric	The number of bits that divide the recorded
Tempor al	Revisit time of sensors

Remote sensing's place in agricultural monitoring

Remote sensing applications are extensively used in agriculture for many purposes, including collection of phonological data on crops, plant identification, assessment of plant health, yield estimation, crop management, irrigation system management, crop stress detection, weed and pest identification, and weather pattern forecasting. Today, UAVs and satellite images plays significant role in agricultural operations by providing real-time & accurate data on trees and crops. UAVs are able to fly in close proximity to different tree species and obtain high-quality photos with a spatial resolution of a few centimetres, which facilitates in-depth examination of tree features at the leaf level (Berni et al., 2009). This capability aids in determining leaf shape, colour, and area coverage, facilitating species identification, monitoring growth, and estimating yield (Tsouros et al., 2019). The advantages of using UAVs for such surveys include lower operational expenses.

Data with multiple bands, such as multispectral and hyperspectral, are helpful in describing plant cover and radiometric response. The multispectral pictures' red and near-infrared (NIR) bands exhibit the highest sensitivity to crop conditions among the spectral data. Chlorophyll, a necessary ingredient for photosynthesis, absorbs the red band, while the structure of cells of leaves reflect the near-infrared radiation. Combining these two bands, in accordance with Bannari et al., enables assessment of plant vigor as well as distinction of vegetation coverings from various types, such as water and soil (Bannari et al., 2009). According to Clevers and Gitelson (2013), red- edge bands offer information on the condition of plant, and vegetation can be distinguished from other objects by using shortwave infrared (SWIR), which displays the vegetation in a darker tone. Table 3 provides some details on the Sentinel-2A bands.

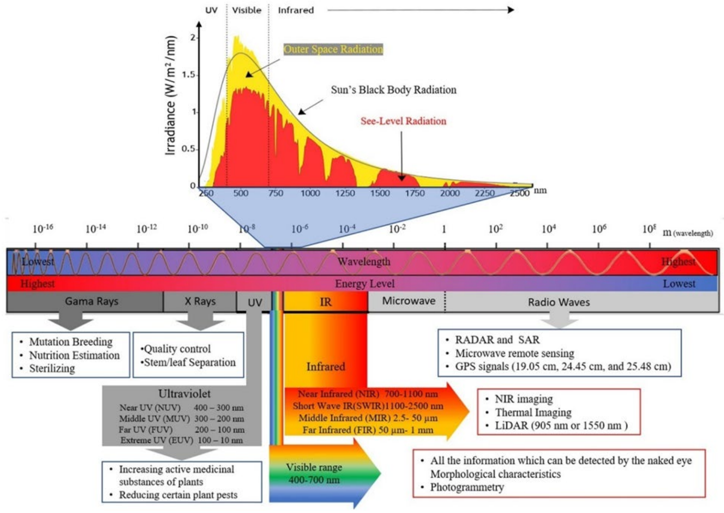

Fig 2 shows the Electromagnetic Spectrum, different wavelengths and regions, bands' energy levels, and some remote sensing applications in agricultural remote sensing applications. 300–2500 nm, the most commonly used region in agricultural remote sensing, is highlighted with solar radiation graphs outside and inside the earth's atmosphere (solar radiation graph modified form), (Verma Samiksha et.al. 2024)

Table 3. Sentinel-2A & 2B bands

Sentinel-2 bands	Sentinel-2A		Sentinel-2B		Spatial resolution (m)	Application
	Central wavelength (nm)	Bandwidth (nm)	Central wavelength (nm)	Bandwidth (nm)		
Band 1 – (Coastal aerosol)	442.7	21	442.2	21	60	Precise aerosol correction of obtained data is made possible by the addition of a spectral band in blue domain.
Band 2 – (Visible Blue)	492.4	66	492.1	66	10	It allows more water to permeate and can distinguish between flora and the surfaces of rocks and soil.
Band 3 – (Visible Green)	559.8	36	559.0	36	10	It has divided the vegetation from the soil and obscured the green reflection peak from leaf surfaces. In contrast to woods, vegetation, croplands without crops & croplands with standing crops, bare fields, urban areas & roads and highways appear brighter (lighter).
Band 4 – (Visible Red)	664.6	31	664.9	31	10	It has a strong chlorophyll absorption region and a strong reflectance region for soils. It distinguishes between soils and vegetation. Not water from woodland, though. The river and the forest were both black. Urban areas, freeways, street patterns, desolate locations have been emphasized by it.
Band 5 – (Vegetation red edge 1)	704.1	15	703.8	16	20	This term "red edge" refers to a place where vegetation reflectance changes rapidly.

Band 6 – (Vegetation red edge 2)	740.5	15	739.1	15	20	
Band 7 – (Vegetation red edge 3)	782.8	20	779.7	20	20	
Band 8 – NIR (Near Infrared)	832.8	106	832.9	106	10	Unlike visible radiation, NIR light can pass via the top leaf layer, bounce off lower layers, and then return via the canopy to the sensor, revealing variations in vegetation density.
Band 8A – (Narrow NIR 1)	864.7	21	864.0	22	20	The purpose of the NIR's 8a band, which is narrow at 865 nm, is to prevent contamination from water vapour while maintaining the band's ability to reflect the NIR plateau for plants and its sensitivity to the amount of iron oxide in the soil. Also, it is employed to calculate the water vapour content.
Band 9 – (Water vapour)	945.1	20	943.2	21	60	It is a water vapour absorption band & is mostly used for atmospheric correction.
Band 10 – SWIR – Cirrus	1373.5	31	1376.9	30	60	It is useful for cirrus detection (cloud detection).
Band 11 – (SWIR 1)	1613.7	91	1610.4	94	20	It is useful for highlighting dense vegetation
Band 12 – (SWIR 2)	2202.4	175	2185.7	185	20	

Source Researcher made table with help of (https://en.wikipedia.org/wiki/Sentinel-2 & https://web.pdx.edu/~nauna/resources/10_BandCombinations.htm)

Table 4. Different band combinations used for vegetation studies

Band combinations	Purpose of band combination	Applications
Band 4, Band 3, Band 2	Use for crop growth, drainage and soil patterns, and vegetation research etc.	The common occurrence of "false colour". Urbanized areas are shown in cyan while vegetation is represented with red hues and soils come in dark brown shades. Clouds, snow or ice are either light blue or white. Unlike hardwoods, evergreens will have a darker shade of reddish colour. This combination of bands is often used to track various stages of crop development, soil drainage patterns and study plant life. Lighter red may indicate grasslands or areas with little foliage while deeper reds normally denote broad leaves and/or more abundant vegetation. These show urban regions that are heavily populated."
Band 3, Band 2, Band 1	Use for detection of Healthy or Poor Vegetation	The combination of bands in "natural color". Because the visible bands are employed in this combination, the colors of the ground features match those of the human visual system. For example, roads are gray, shorelines are white, freshly cleared areas are very light, healthy vegetation is green, & poor vegetation is brown and yellow. This band combination provides the most possible water infiltration and the highest quality

		sediment and bathymetric data. It is also used in urban studies. This combination is more difficult to detect cleared and thinly vegetated areas than 4 5 1 or 4 3 2 combinations. Snow and clouds look the same and are hard to tell apart. Observe that differentiating between vegetation kinds is more difficult than with the 4 5 1 combination. Shallow water and soil cannot be distinguished by the 3 2 1 combination in addition to the 7 5 3 combination.
Band 7, Band 4, Band 2	Use for detection different type of Vegetation	This mixture penetrates smoke and airborne particles to produce a "natural-like" rendering. In seasons of intense growth, healthy flora can reach saturation, appearing as bright green. Grasslands will also be green, while places with scarce vegetation will be represented by orange and brown hues, and pink areas by bare soil. Water will be blue, and dry vegetation will be orange. A rainbow of colors highlights the sands, soils, and minerals. This band arrangement conjures up powerful images of desolate landscapes. It is helpful for research on wetlands, agriculture, and geology. It would become red if only there were fires. Used in fire control applications the two are combined to map out the burned and the unburned forest territories after the fire. As if urban regions were some kinds of shades of pink. As the name suggest, grasslands are characterized by the presence of grasses, which gives it pale green colour. The lighter green color within the city represents the areas of the land that are usually natural like the green areas within the city; these are the area occupied by parks, cemetery, and golf courses. Specifically, the olive green to brilliant green color implies the presence of forest; coniferous forests will be deeper in color as compared to the deciduous forests.
Band 5, Band 4, Band 3	This combination is helpful for vegetation studies	This combination gives the consumer a lot of information & color contrast, just like the 4 5 1 combination does. Rich greenery and purple soils are signs of healthy vegetation. The combination that employs the most agricultural information, 5 4 3 uses TM 5, whereas the combination that uses TM 7 incorporates the geological information. In addition to being widely employed in the fields of insect infestation and wood management, this combination is helpful for vegetation studies.
Band 5, Band 4, Band 1	This combination is helpful for vegetation research.	The healthy vegetation in this combination will resemble that of the 7 4 2 combination, with the exception that the 5 4 1 combination is better suited for agricultural research.
Band 7, Band 6, Band 4		In this band green hue denotes the presence of flora. Water sources are shown in black or dark-blue. Urban areas and towns are dispersed throughout ranges from white to purple to cyan. If the image appears red, it means that the sensor captured an image of a volcano, forest fire, or solar panel field.
Band 8, Band 4, Band 3	False Colour Infrared (FCC)	It is a highly common combination used in studies of vegetation, where darker red tones show areas with broad leaves and lighter red tones show grassland and areas with a low density of vegetation.
Band 8A, Band 11, Band 2	Agriculture	When band 8A, band 2 & short-wave infrared (SWIR- Band 11) are all used together, it makes it easier to find different stages of tree species, which helps in this case with identifying tree species.
Band 11, Band 8A, Band 4	Vegetation Analysis	This combination reveals healthy vegetation to be a bright green colour, and the soils are a mauve colour. So, it is used for separating the vegetation from the soil.
Band 12, Band8A, Band4	Shortwave IR Combination	This combination of bands can be used to see changes in the health and stress of plants, since coniferous trees look rich and deep green and deciduous trees look bright green.

Source: Researcher made table with help of (https://eos.com/blog/band-combinations-for-landsat-8/ & https://web.pdx.edu/~nauna/resources/10_BandCombinations.htm)

Therefore, all the mentioned points indicate that remote sensing technology is important in the agricultural industry with a special reference to monitoring and identifying different trees and crops. Modern technology advancement has provided farmers with an opportunity to monitor their fields and also check on trees and crops in the process making management decisions.

3.3. CHECKING DIFFERENT SPECTRAL INDICES

Get several spectral ratios of satellite data which are helpful in vegetation and crops health studies. There are six spectral indices:

NDVI (Normalized Difference Vegetation Index): Approximately measures the condition/ health of vegetation.

NDWI (Normalized Difference Water Index): Evaluates the water status of plants and their efficiency in using the water available in the environment.

NDMI (Normalized Difference Moisture Index): It indicates the moisture content of the vegetation cover.

MCARI (Modified Chlorophyll Absorption Reflectance Index): Assesses the chlorophyll content.

Cl-Red Edge (Chlorophyll Red Edge): Chlorophyll and vegetation health affected by stress. S2REP (Sentinel-2 Red Edge Status): It indicates possible variations in the healthy status of vegetation.

3.4. SPATIOTEMPORAL ANALYSIS OF THE STUDY AREA, BY COMPARING IT WITH HEALTHY AND DISEASE INFECTED AREAS, WHERE THE AGRICULTURAL FIELD WAS DIGITIZED.

Divide the AOI into healthy and infected areas using existing field knowledge. This process involves outlining the degree of infection on the ground or referring to data collected through high-definition images. Also random points should be generated in the digitized healthy and infected areas. These points will be used in the sampling and extraction of the pixel values of the spectral index.

3.5. PLACE THE POINT LAYER ON TOP OF THE INDEX AND THEN OBTAIN THEIR PIXEL VALUES

Overlay the generated set of random points on each of the six layers of the spectral index to obtain analog pixel values at the locations of the points. This results in a database of spectral features of each point. According to the chosen task, extract the attribute data in tabular form with the attribute "class" containing the infected/not infected values. Organize a table from the extracted pixel values, including an additional column: 'class', which indicates whether each point should be considered as infected or not infected by the virus according to the initial digitization.

3.6. THE LAST FIVE STEPS INVOLVE THE DESIGN AND DEVELOPMENT OF THE DEEP LEARNING ANN MODEL AND THE TRAINING OF THE MODEL.

An ANN framework needs to be designed to implement the classification of infection level on an ad-hoc basis obtained from the spectral index data. Apply the ANN algorithm using the tabular data that is a list of spectral index values with a corresponding list of infection conditions.

3.7. ASSESSING THE ACCURACY OF THE DEEP LEARNING ANN MODEL AND CROSS VALIDATION OF THE SAID MODEL.

Test the suggested cross-validation methods on the model, which will prove useful in understanding the model's ability to perform well on data on which it was not trained. Then calculate the values of accuracy rate, precision, recall rate and other related factors that determine the model's ability in classifying the infection.

This research thus employs a hierarchical non- linear-regression technique to mitigate this challenge in an endeavour to enhance the crop yield performance using actual primary data & secondary data on Indian agriculture yields particularly wheat with related yellow wart disease to help farmers' economically with betterment of conditions.

4. LITERATURE REVIEW

Monitoring and predicting the local crop production is an effective way to address the problems of food security on the global level. It is documented that remote sensing data have potentiality of providing timely, synoptic and repetitive observation of the surface of the earth at multiple geographical scales. Optical remote sensing using satellites in remote sensing technology satellites observe the surface of the Earth for the reflected electromagnetic energy.

4.1. CROP YIELD PREDICTION METHODS

Datta Ayon et. Al. (2023). Using the information available in the literary sources to the extent of the works conducted and the availability of data, he identified that different features in the chosen articles were used. However, it was noted that characteristics that were used in each of the research to predict the yield using machine learning were not the same. Scale was also different as well as location and the type of crops being grown during the research. This is the case because the features chosen reflect the nature of the study goals and data available for analysis. The study also realized that there was no necessarily an improvement in yield prediction outcomes associated with a larger model feature size. Hence, it is necessary to compare performance between the model with more characteristics and the model with fewer characteristics. The research used a variety of algorithms & findings showed that no single model consistently performed better than others. On the other hand, certain machine learning models were applied more often than others. Models that were most frequently utilized were gradient boosting tree, random forest, neural networks & linear regression. In order to identify the optimal model for prediction, the majority of the studied research investigated the performances of several machine learning models. Nevertheless, various types of algorism were also addressed to this problem. According to him, this study will help in the creation of new lines in exploring the promotion of yield prediction in agriculture.

Tripathi Padmesh et. al. (2023). Several agricultural sectors, including yield prediction, weed and disease detection, water and soil management, livestock production, etc., have used machine learning (ML) and its variations. Agriculture has benefited greatly from machine learning techniques, which have raised the caliber and output of agricultural goods.

Burdett Hannah et. al. (2022). He compare methods for calculating the correlation between topographic features and soil in order to forecast crop yield utilizing analytical methods and high- resolution data.The study was carried out on a multiple field dataset situated in Southwestern Ontario, Canada. In this region, not many studies have evaluated the effects of machine learning (ML) and precision agriculture applications on the link between soil property and yield. This study took into account the following characteristics: pH, the amount of soil organic matter (OM), the cation exchange capacity (CEC), the phosphorus content of the soil test, elevation, zinc (Zn), potassium (K), and the topographic moisture index. To find techniques that might link crop yields and soil characteristics on a subfield scale (2 micrometers), multiple linear regression (MLR), artificial neural networks, decision trees, and random forests were compared. With an R2 score of 0.94 for soybeans and 0.85 for corn, random forests proved to be the most accurate in yield prediction. MLR performed the worst, with R2 values of 0.45 for soybeans and 0.40 for corn.

4.2. DEEP LEARNING TECHNIQUES ARE PLAYING AN ACTIVE AND SIGNIFICANT ROLE IN AGRICULTURAL APPLICATIONS AS SHOWN IN BELOW POINTS:

Meghraoui Khadija et al., (2024). Thus, this work provides a literature review to respond to four critical research questions concerning deep learning- based agricultural yield prediction. This entails applying a set of procedures on the literature to look for the information that is relevant. According to the author, it is therefore understood that deep learning models possess certain characteristics that make them different from other classes of models especially in Intelligent Agriculture. First of all, one needs to take into account the kind, quantity, and sufficiency of the data that will be applied. More sophisticated tools such as data enhancement techniques and transfer learning can be applied to a manual data/image set. In addition, the peculiarity of the crop and the architecture chosen for this setup are critical for collecting dense data that improve the model. There is a challenge of interpretating these models because their ‘black box’ components are not easily understood as to what causes them to output what they doThe systematic review shows that in research articles, authors employ a range of deep learning architectures; Convolutional neural networks of various dimensions, ranging from 1D to 3D; Long Short Term Memory Networks; famous deep neural networks; and other kinds of Recurrent models such as Gated Recurrent Units. Higher levels of hybrid solutions are also being seen more frequently. The evaluation also reveals that crop yield prediction investigations primarily concentrates on cereals, while satellite or drone images act as the most used information.

Chang Xuning (2024). Thus, as a study that aims to show the possibility and usefulness of deep learning in rice production forecast, this work wishes to add to ongoing initiatives toward food sufficiency and proper agricultural administration. The findings of the study also have broader implications to the applicability of other deep learning methods in other fields of natural resources management and agriculture. To conclude, precision agriculture is important always, especially when it comes to the global food security. Regarding yield prediction, the models such as LSTM and GRU turned out to be very effective in the research area. This assists the farmer in making the right decisions concerning their crops & use of resources. In addition, the described models have one advantage for precision agriculture applications – the ability to process time series data. Thus, the prospects of developing even higher-degree deep learning models for use in agriculture are vast. In case of agricultural production prediction, transformers for instance may be fine-tuned. These models have been evidenced to hold potentials in natural language processing reveres. However, issues that relate to data limitations in agriculture could be addressed by using generative models which entail Chat GPT in the creation of artificial data for deep learning model development. Overall, this work has shown that deep learning can be applied successfully in agriculture & pointed to the further work's relevance in this area. It is possible to set more sustainable and effectively means of agriculture practices by using the machine learning to enhance the progress; this will help the environment and the global food security.

Attri Ishana et.al. (2023). In this study, the authors stress how greatly DL approaches can transform the agriculture industry. Out of all the areas, the five basic areas have been defined by the research study as having implemented DL which includes crop yield prediction, stress detection in plants, weed & pest identification, disease identification, and smart farming. Smart farming is a separate category where soil analysis, seed analysis and water management fall in. It is possible to state that the investigation proves the efficiency of DL's impact on raising agricultural output and the financial results.

4.3. TIME SERIES ANALYSIS IN AGRICULTURE

Yoo Tae-Woong et. al. (2020), The purpose of their research is to stabilize supply and demand using a seasonal long short-term memory (SLSTM) technique for anticipating agricultural commodity sales. Utilizing the week, month, and quarter seasonality attributes as further inputs to historical time-series data, the SLSTM model is trained. Both separately and in combination, the seasonality attributes are input into the SLSTM network model. Root mean squared error (RMSE), Mean absolute error (MAE), as well as normalized mean absolute error (NMAE) were the three performance measures used to evaluate the performance of the proposed SLSTM model with that of auto_arima, Prophet, and a conventional LSTM. The suggested SLSTM model has an error rate that is much lower than that of other classical approaches, according to the experimental findings.

AERI Admin, (2021), It is possible to develop a model that defines the data in a way that facilitates estimate, analysis, and regulation by having a thorough understanding of the mechanics underlying time series. An asset, security, or economic variable's historical changes can be found via time series analysis. In addition, it can be applied to compare changes in one variable to changes in another over the same period of time. . It is impossible to dispute the significance of time series analysis for agribusiness.

4.4. FUSION OF REMOTE SENSING AND AGRICULTURE

Victor Nancy et. al. (2024), In order to address the varied agricultural practices in the Industry 5.0 (I5.0) age, this study offers a thorough survey on remote sensing technologies along with associated aspects. Additionally, he goes into great detail on the different uses for I5.0-enabled agricultural remote sensing. In conclusion, he addresses various obstacles and concerns pertaining to the incorporation of I5.0 technologies in agricultural remote sensing. This thorough analysis of remote sensing in the context of Industry 5.0 agriculture provides insightful information about the state, obstacles, and prospects for progress in the application of Industry 5.0 concepts and remote sensing technologies to agriculture, opening the door for further study, creation, and application methods in this field.

Do Anh Ngoc Thi, (2024), using a hybrid Principal Component Analysis-Support Vector Machine (PCA-SVM) model using SPOT satellite images, the current study's main goal is to identify areas that are vulnerable to flooding in order to assess the impact of floods on Hanoi City's agricultural land use. AUC = 0.921 and R2test = 0.904 indicate an excellent model performance in the prediction outcomes. 55.882% of the total area is categorized as high to very high flood vulnerable, whilst 10.357% and 6.278% of the area are categorized as low and very low flood risk, respectively. Combining satellite data with the PCA- SVM model to create zoning maps that are vulnerable to flooding provides important information to support efforts to reduce flooding.

4.5. COMPRESSION BETWEEN LINEAR REGRESSION, DECISION TREE REGRESSION, GRADIENT BOOSTING REGRESSION, RANDOM FOREST REGRESSION, XGBOOST REGRESSION, AND VOTING REGRESSION

Panigrahi Bharati et. al. (2023), The purpose of this research study is to examine the application of machine learning techniques in the development of an accurate crop production forecast model for groundnut, maize, and Bengal gram in the Telangana region of India between 2016 and 2018. The Random Forest Regressor fared better than the other models, with a Cross Validation score of 0.6087 and a Mean absolute error (MAE) of 468.16. The three metrics that the authors employ to assess the model are the Cross Validation Score, R2 Score, and Mean Absolute Error. These are as follows:

- **Mean absolute error:** Over the course of the whole array, the absolute differences between each observation's estimated and actual values are added, and the result is divided by the total number of observations in the array to determine the mean absolute error (MAE). The MAE will be employed to ascertain the degree to which the mistakes in a set of estimations differ between predictions. Since the result is negatively oriented, lower numbers are preferred.
- **Mean squared error:** An estimator's Mean Squared Error (MSE) quantifies the average squared error, or the discrepancy between the estimated and real values. MSE is not specified. In simple terms, 0 is the optimum value. Given that there is no correct answer, the MSE aids in selecting prediction models.
- **R2 score:** The coefficient of determination, or R squared, is a statistical measure that is derived from the variance in the predictions. It computes the relationship between an independent variable's movements and the movements of a dependent variable. It won't let us know if the chosen model is bad or good, or if the projections and data are biased. Moreover, there is no correct response when determining the appropriate R2 score. 100% indicates an ideal correlation. But there are also as useful models with low R2.
- **Cross-validation score:** In applied machine learning, cross-validation is most frequently used to assess a machine learning model's suitability for unidentified data in order to avoid overfitting. It is a technique for evaluating machine learning models that entails training multiple models on corresponding subsets of the input data and then analyzing them.

Creating the best Machine Learning (ML) model feasible for predicting agricultural yields for three distinct crop types—betel gram, groundnut, and maize—is the main goal of this project. Six distinct types of alternative regression models, Decision Tree Regression, including Linear Regression, Gradient Boosting Regression, Xgboost Regression, Random Forest Regression, and Voting Regression, were used to train the data in order to produce accurate crop yield estimates. The values for the three metrics—Mean Absolute Error (MAE), R2 score, and Cross-Validation score—for each of the six models listed above are shown in Table 3. These standards are essential for assessing models and determining which model is most appropriate for the final forecasts.

Table 1. Metrics of models trained

Regression Mode	**Mean Absolut**	**Mean Square**	**R2 Score**	**Cross-Validatio**
Linear Regre	1121.60	1384.58	0.347	0.2022
Decision Tree	745.75	1015.52	0.4516	0.3425
Gradient Boosti	532.34	848.88	0.7544	0.6009

Random Forest Regression	475.17	851.30	0.7732	0.6158
XGBoost Regression	488.32	769.49	0.8334	0.5026
Voting Regression	549.02	828.35	0.7599	0.5899

The Department of Agriculture and Cooperation, Government of Telangana, listed the Open Data Portal of the State of Telangana, India, where the data for this study was gathered. In order to estimate the crop yield, this study placed a strong emphasis on the adaptation of machine learning (ML) techniques. Six different supervised-based learning regression models were trained on: Linear Regression, Gradient Boosting Regression, Decision Tree Regression, Xgboost Regression, Random Forest Regression, and Voting Regression. Of these, Random Forest Regression and XGBoost Regression were the two most accurate. Our observations indicated that the XGBoost Regression model had a low Cross Validation score and a high R2 score, indicating overfitting. Furthermore, after parameter adjustment, the Random Forest Regression model surpassed the XGBoost Regression model with an MAE score of 468.16, an MSE score of 825.29, an R2 score of 0.7952, and a Cross-Validation score of 0.6087 respectively. Images of the field and crop can be subjected to a variety of Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision (CV) techniques to identify any diseases or weeds that may be present, which could negatively impact the crop's quality. If weeds are present, the healthy crops can be quickly isolated from the diseased ones.

5. ARTIFICIAL INTELLIGENCE (AI)

Computer-controlled robot, Programming a computer, or giving software intelligence to think on their own and like humans is termed as Artificial Intelligence or AI. AI is created based on the studies of people's thought, knowledge acquisition, decision making, and solving activities. Then, smart systems and software are designed based on such realizations. AI usage is quickly and steadily increasing across lots of fields with the sphere of agriculture being one of the most significant where AI is used extensively to monitor vegetation. In the modern world, farming incorporates the use of drones whereby they are used in capturing quality images that help in keeping track of crops as well as the analysis of the field in order to obtain useful farming details. Besides, it has been observed that majority of the agricultural insurance companies use satellite-based vegetation monitoring systems. This enables crops to be seen, their growth and health status determined as well as their ripeness for harvesting (L. Ma. et al. 2019).

Machine Learning (ML) in agriculture boosts yield and productivity and decreases the cost of production in farming. Through imagery used in remote sensing, one is able to determine the various crops that are grown in various part of the world. There are several approaches presented in the literature to recognize the crop species by using UAV and satellite images. ML techniques and Deep Learning (DL) techniques are the part of AI, Like Figure 2:

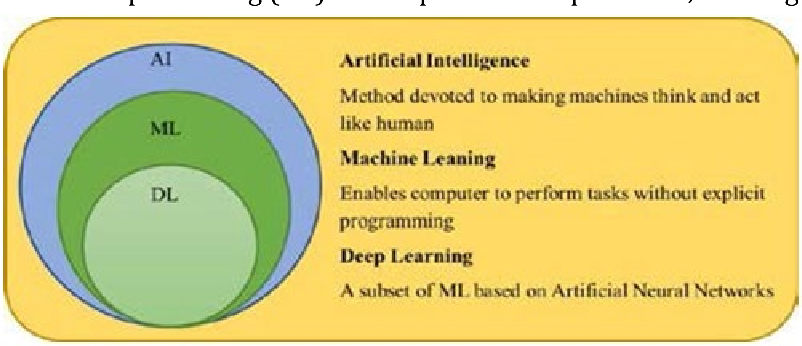

Figure 3 Relation of AI with ML and DL (Federchuk Mikayla, 2022)

5.1. OVERVIEW OF DEEP LEARNING (DL)

DL is a subset of AI, which entails utilising multilayer artificial neural networks to make effective decisions after learning from vast data. They utilize layers of interrelated neurons and learn to extract certain characteristics from the entered data, imitating the human brain's structure and operation. DL algorithms allow the identification of what the data represents, how it can be categorized, and other intricate structures with no need for direct programming. They are top-notch where there is a reformulation of problem solving, pattern recognition, and making accurate predictions, especially with large datasets such as images, words, and sounds.

5.1.1. ADVANTAGES OF DEEP LEARNING

Another one is its capability of performing feature engineering in fluids, which makes DL one of the most distinctive MI methods. Thus, to let the DL models learn more times faster, these models scan the data in search of relevant features to incorporate. In these models, multiple layered hidden layers neural networks are applied. There are numerous types of deep neural networks, yet one of the most efficient for the grid-like input such as images are convolutional neural networks or CNN. Local fields of reception are convoluted with filters (kernels) in CNNs to enable the network to learn its own spatial hierarchies of data. Also, it is common to incorporate pooling layers within CNNs to scale down feature maps so as to relieve the computational burden.

6. TIME SERIES ANALYSIS

Statistical analysis belonging to the time series analysis deals with the data that has been collected at different points of time in the past. This in a nutshell means just looking at a sequence of variates that have been quantified at uniform time intervals. It could for instance be stock prices, weather conditions, sales data, or any other data including the physiological data like one's pulse rate over time.

Main goals of time series analysis are to comprehend basic properties and characteristics of this data and to develop prognoses or estimate values by the basis of previous data and observations. The following are some crucial elements of time series analysis:

6.1. TREND ANALYSIS

Trend analysis is basically the process of observing movements of data as a way of studying trends that are normally seen in data patterns. This is important when evaluating or predicting changes in variables of interest which in turn is important in decision making, forecasting and effective implementation of business strategies. Here's a detailed explanation of trend analysis, including its types and modeling:

The activity of collecting information and seeking for this pattern, or trend, in the data is referred to as the trend analysis. This is useful in estimating future occurrences given the past occurrences of events. Trends refer to the general movement patterns that are observed with regard to any given data points over some duration of time.

The major aspects of trend analysis are as follows:

- **Data Collection:** Data collection is the first step in getting information from the relevant past periods. This information might have been derived from the following factors; climatic factors and the soil type.
- **Visualization:** The identification of trends during the analysis through graphing of the collected data on a graph. Different kinds of chart used include line chart, bar chart and scatter chart.

Identification of Trends:

Stable Trend: Sometimes the data points without showing high and low varies around a fixed mean value. This means that there is no pattern as to what is happening in the data.

Upward Trend: When the data featured an increase trend line on the y- axis or when the data increased over time. This can be used to show increase or change in the observed variable.

Downward Trend: When the data trend depicted is lower in the succeeding years than the previous year. This might mean a decrease or bringing down of the observed variable, or just that what is being observed less frequently.

6.1.1. TYPES OF TRENDS

Linear Trend: A condition in which discrepancy between current and past state remains constant over time and depicts a straight-line movement. Yes it is, for example, you may have a upward mobility in the company while the other employees may experience a downward momentum in the same firm.

Non-linear Trend: Curved trends which are trends that bend and go upwards or downwards in a non-linear manner showing that the rate of change is constant.

Seasonal Trend: Those that occur cyclically, say on a daily, weekly, or, monthly, or other short cycle frequency.

Cyclical Trend: Such changes can be described as long-term, which are introduced in relation to cyclical changes in the economy, or the business world, which is more than a year.

Trend analysis is a significant technique of examining and forecasting the alterations in the data that are moving in cyclic or periodic trends. Thus, defining stable or upward or downward trends means that organisations and individuals can make decisions about choices of actions and strategies based on firm factual patterns.

6.2. AUTOCORRELATION

It is a statistical measure that signifies the amount of relatedness between a variable's current value and the equivalent earlier values at the different time lag. It determines the extent of association and dependency of a data point in a time series. Understanding of autocorrelation implies the ability to uncover the connections between the data and the patterns as well as trends present in the data.

6.2.1. UNDERSTANDING AUTOCORRELATION

Temporal Dependence: Autocorrelation explores the presence and strength of the link between a variable's current state and its past state. which is further used in the projection techniques. In this regard, methods like exponential smoothing, machine learning models & ARIMA used in the forecasting process to help the organizations with the future expectations and occurrence of different environments.

Time Lag: Autocorrelation can be calculated for different time differences, or lags between observations. Autocorrelation output shows that k percent by percentage has a positive value, which means that past values exert an impact on the current values after k time periods.

Patterns in Time Series Data: This makes it possible to detect patterns, trends or cycles within the data, through using autocorrelation. Time series is particularly used to identify seasonality and trends' continuation.

Autocorrelation Function (ACF) Plot: The ACF is a graphical display of the autocorrelation at different time steps; it is sometimes also referred to as correlogram.

6.2.2. FORECASTING

Forecasting can be explained as the process of extrapolating the values of future periods in a time series data on the basis of available patterns and trends. It is used commonly in diverse sectors such as environmental conservation, economic development, marketing, and finance since it enable sound decision- making and planning. Remarkably, time series analysis forms the basis of forecasting since it aids in determining patterns in data that are later used by forecasting techniques.

Forecasting is widely used in different domains for expecting future trends and organizing decision- making and strategies. The component of time series analysis enables the discovery of trends in past data, which is further used in the projection techniques. In this regard, methods like exponential smoothing, machine learning models & ARIMA used in the forecasting process to help the organizations with the future expectations and occurrence of different environments.

6.3. MODEL EVALUATION (MAE) AND OTHER FORMULAS

Evaluation metrics are very important to give an idea about the performance of the machine learning model. Here's an overview of some common metrics, including Mean Absolute Error (MAE), and their formulas:

6.3.1. MEAN ABSOLUTE ERROR (MAE)

When direction does not matter, the mean absolute error or MAE determines the average of the errors that exists in given forecasts of a set. The weight estimated for any of the individual differences includes the mean of the absolute differences between observed and the predicted values over the test sample.

Formula

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

Where:

(n) is number of observations.

(yi) is actual value.

(yˆ i) is predicted value.

6.3.2. MEAN SQUARED ERROR (MSE)

MSE is a measure of average value of square of mistakes. It is notably more sensitive to outliers as compared to MAE because the use of squared errors makes proportionately larger errors much larger.

Formula

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

6.3.3. ROOT MEAN SQUARED ERROR (RMSE)

RMSE is the square root of MSE likewise ME is the square root of MSE as well. Its measure is the sample standard deviation of differences between the actual and expected values.

Formula:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

Mean Absolute Percentage Error (MAPE)

A measure of accuracy used is presented in percentage through the use of the MAPE formula. It is relatively easy to understand because it quantifies the inaccuracy in terms of the actual numbers.

Formula:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \text{ x } 100$$

6.3.4. R-SQUARED (COEFFICIENT OF DETERMINATION)

The amount that the dependent variable can be explained by the independent variables is given by the R-square statistical measure. Guess work is low when models predict the dependent variable and range from 0 to 1, where 1 means perfect model.

Formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Where (y) is the mean of the actual values.

6.3.5. ADJUSTED R-SQUARED

The Adjusted R-squared penalises the original statistic in regard to the number of predictors in the model. They describe the number of the predictors and is always smaller than R-squared.

Formula:

$$\text{Adjusted}\,R^2 - 1 = \left(\frac{(1-R^2)(n-1)}{n-k-1}\right)$$

Where (k) is the number of predictors and (n) is the number of observations.

6.3.6. F1 SCORE

An F1 score is a weighted mean of precision and recall and is the best choice in classification problems to balance between those two important parameters.

Formula:

$$F1 = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right)$$

Where:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad \text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

6.3.7. ACCURACY

Accuracy, which measures the proportion of correctly classified observations, is used when dealing with categorization issues.

Formula:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

6.3.8. PRECISION

Precision describes the percentage of positive identifications that were truly correct.

Formula:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

6.3.9. RECALL (SENSITIVITY)

It measures the ability of a model to find all the relevant cases within a dataset

Formula:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

These metrics provide different ways of measuring and understanding how well machine learning models perform in distinct scenarios and on various data sets.

Statistical models are needed to understand the relationships among key components of agricultural systems. Time series forecasts are fundamental for effective cropping programs that increase agricultural productivity. These assumptions are typically based on time series data collected over many years. Time series involve repeated observations "in time" of various data items. The development of models, the calculation of parameters, and the future prediction of its value are the main objectives behind time series analysis. The three dimensions of a timeline are continuity, temporality, and relativity. Seasons can change over time and can be structured or regular. The trends also show something else that keeps coming. Autocorrelation is a local phenomenon: it is positive when deviations from trend lead to similar deviations while negative autocorrelation is extremely rare.

Different techniques can be used to predict something depending on the target and its importance. Common images include:

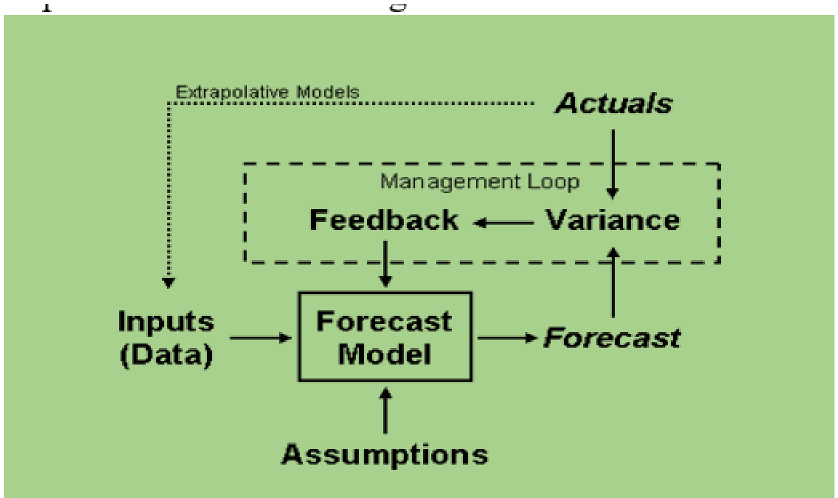

Figure 3 updated diagram of forecast model

Figure 3 updated diagram of forecast model

Source http://www.practicalforecasting.com/forec ast-structure.html.

- Cultural perspectives
- Nonlinear Models
- Spline or Piecewise Regression Models
- Structural Time Series Models
- Forecasting using Artificial Neural Networks (ANN)

6.4. CNN-RNN MODEL

The process of predicting crop yields is very difficult due to many factors that influence it such as environmental conditions, crop genotype, management practices and interactions between them. In this article, a deep learning framework using "convolutional neural networks (CNNs) and recurrent neural networks (RNNs)" is proposed for the prediction of crop production based on environmental data and management techniques. For the years 2016, 2017, and 2018, the CNN-RNN model was used to predict corn and soybean yields in all thirteen states that make up the Corn Belt in the United States. Other popular methods included LASSO, "deep fully connected neural networks (DFNN)", & random forest (RF). Compared with previous studies, this new model performed significantly better with a "root-mean-square-error (RMSE)" of 9 % & 8% of their respective average yields. The CNN-RNN model has three characteristics that suggest it could be useful for future research on predicting agricultural productivity. (1) It records the time correlation of environmental conditions and the genetic development of seeds over time without requiring genotype information. (2) The model has also demonstrated that it can be applied to new or untested cases with little loss in accuracy. (3) If combined with backpropagation technique, the model can indicate what extent soil characteristics, crop management practices, weather patterns, and crop factors contribute to variations in crop yields.

Soil, weather, management, and yield performance were the four datasets analyzed in this study. Unfortunately, there was no genotyping data available for public use to supplement these datasets. The yield performance dataset comprised observed average maize and soybean yields for corn 1,176 counties for corn and 1,115 counties for soybeans between 1980 and 2018 which covers all thirteen states constituting the Corn Belt. In Iowa Missouri Minnesota Nebraska South Dakota Kansas North Dakota Ohio Kentucky Wisconsin Michigan; corn & soybeans are grown here. Management data started every year from April recording weekly cumulative % of planted fields across each state. Both yield performance & management data were provided by United States National Agricultural Statistics Service (USDA-NASS, 2019).

Six weather variables like- solar radiation, precipitation, snow water equivalent, minimum temperature, maximum temperature & vapor pressure, were included in the weather dataset's daily

records. Daymet (Thornton et al., 2018) provided data, which had a 1 km 2 spatial resolution. The soil dataset contained measurements of “saturated volumetric water content” at different depths (0–5, 5–10, 10–15, 15–30, 30–45, 45–60, 60–80, 80–100, and 100–120 cm), wet soil bulk density, dry bulk density, clay percentage, organic matter percentage, hydraulic conductivity, pH & sand percentage. In addition, the following four soil characteristics were solely measured at the surface: crop root zone depth, average national commodity crop productivity index for all crops, field slope % & national commodity crop productivity index for corn. With a same 1 km 2 spatial resolution, this soil data was obtained from Gridded Soil Survey Geographic Database for United States (gSSURGO, 2019).

By employing a grid map approach, the researcher was able to select multiple weather & soil samples from each county & then average these data to generate representative samples for both soil & weather. For certain places in soil data, there were 6.7% missing values. These were imputed using mean of same soil variable from neighbouring counties. Similar to this, 6.3% of the management data's missing values were imputed using the management variable's mean from other counties in same year. We investigated other imputation techniques like median & mode, but mean method produced most accurate results. While there were no missing numbers in the weather data, the daily data was deemed to be excessively detailed. As a result, the researcher reduced the dimensionality from 365 to 52 by averaging the daily data into weekly averages. The first layer of “neural network model's” trainable parameter count was greatly reduced by this pre-processing stage.

Linear & nonlinear effects of weather & soil data, respectively, were captured in this research by developing the W-CNN and S-CNN models. The temporal dependencies of meteorological data were captured by the W-CNN model using one- dimensional convolution, & spatial dependencies of soil data obtained at various subsurface depths were captured by S-CNN model using same one- dimensional convolution technique.

Time dependencies of crop yield across a number of years were intended to be captured by RNN model. Two opposing data provided the basis for use of RNN model: over previous forty years, yields of both corn & soybeans have trended upward. A directed graph is used to express temporal dependencies in a particular kind of artificial neural network called an RNN. In order to capture temporal dynamics of crop yield resulting from genetic advances, a dedicated RNN model was created. These RNNs were enhanced by the addition of LSTM cells, which are carefully designed recurrent neurons that progressively capture input dependencies. Compared to previous time series models, LSTM networks have demonstrated superior performance in a range of sequence modeling applications, and they do not require the definition of the nonlinear function to be estimated. The RNN model, comprising k LSTM cells, forecasted a county’s crop yield for year t by utilizing data from years t − k to t. Cell was fed average yield data (for all counties in same year), management data & fully connected (FC) layer's output, which retrieved significant features from weather & soil data used to process tW-CNN & S- CNN models. Interestingly, despite the fact that soil data is typically static, S-CNN & FC models were created expressly to transfer soil data that was measured at surface straight to LSTM cells.

Despite absence of weather or soil data, the RNN model can nevertheless estimate crop output based on historical trends when it receives historical average yield data as input. For yield prediction, if year t is the target year, then in test phase, one can replace the average yield of year t, $\bar{Y}$ t, with $\bar{Y}$ t−1 & replace unobserved part of Wt's weather data with the weather data that is predicted. Still, since all of the input data is available during the training phase, this kind of substitution is not necessary.

Therefore, combining environmental data and management techniques, a deep learning-based approach to crop yield prediction was proposed in this study, which accurately anticipated maize & soybean yields across entire maize Belt in United States. This methodology was noteworthy because it went beyond simple prediction and offered important insights into yield prediction, including the significance of factors over various time periods. The proposed method demonstrated significant advantages over existing popular approaches, including LASSO, random forest & "deep fully connected neural networks (DFNN)". "Recurrent neural networks (RNNs) and convolutional neural networks (CNNs)" are combined to create the model. The CNN component was supposed to capture the spatial relationships of soil data at various depths & internal temporal dependencies of meteorological data. With ongoing advancements in plant breeding as well as cultivation techniques, crop yields have been steadily increasing over time. This tendency was meant to be captured by the RNN component. The model demonstrated considerable sensitivity to a range of parameters, such as weather, soil, management & demonstrated the ability to accurately estimate yields in untested situations, suggesting its potential for use in upcoming yield prediction tasks.

The "black box" aspect of deep learning models is one of their primary problems. Feature selection was carried out using the backpropagation approach, based on the trained CNN-RNN model, in order to improve interpretability of proposed model. A significant innovation of this study is the methodical technique that was used to effectively assess the individual effects of soil conditions, meteorological components, and management variables. It also pinpointed the times during which these variables gained significance.

6.5. DIFFERENCE BETWEEN CNN AND RNN

6.5.1. CONVOLUTIONAL NEURAL NETWORK (CNN)

Convolutional neural networks (CNNs) are mostly used for processing multidimensional data, which includes picture data. CNNs use a variety of building blocks, including layers of convolution, layers of pooling, and fully connected layers, to itself and automatically acquire spatial hierarchies from data through backpropagation.

Key Characteristics of CNNs:

- **Spatial Data Processing:** CNNs are exceptionally well-suited for capturing spatial dependencies and structures in data, making them ideal for tasks like image recognition, image segmentation & object detection.
- **Convolutional Layers:** In order to identify features like borders, textures, and other complicated structures in higher layers, such layers apply convolution processes to the input, essentially scanning it with filters.
- **Pooling Layers:** These layers reduce dimensionality of data, helping to extract dominant features & making model computationally efficient.
- **Fully Connected Layers:** As for the features that the pooling and the convolutional layers have extracted, these layers, therefore, make the final decision for the entire network. Higher order thinking is performed here.

  In crop yield prediction, CNNs are used to get spatial-temporal relations of environment information such as climate and soil features got at different levels of depth.

6.5.2. RECURRENT NEURAL NETWORK (RNN)

Thus, keeping some sort of memory of the previous inputs in the sequence, there is a “Recurrent Neural Network (RNN)”, which is a type of neural network designed to operate on sequences. RNN is useful in situations where sequence of data points is relevant as is seen in speech recognition, predictive time series, and natural language processing.

Key Characteristics of RNNs:

Sequence Modeling: RNNs are used for capturing temporal relations and sequential characteristics in the data in uni-directional as well as in bidirectional manner. They are supposed to be able to work through sequence of different length and process \emph{one element at a time}, while having a state which contains information about the previous inputs.

Recurrent Connections: In contrast to the feedforward neural networks, the RNNs have feedback-loop connections which are used to maintain data. That is, the network can maintain a state which can encode the historical data due to this looping method.

Long Short-Term Memory (LSTM): LSTM is a kind of RNN which is used to solve the long- term dependency problem. It is due to its more complex structure that has gates to control the data flow Long Short-Term Memory Banks (LSTMs) are also capable of learning the long term dependency without facing the vanishing gradient problem.

In terms of crop yield prediction, RNNs particularly the LSTMs are helpful to capture the temporal dependencies of the yields over time. They are meant to factor in the impacts that trends and patterns have over the different years in growing seasons.

Thus, CNNs are designed for working with spatial data and are most often applied to problems related to images or containing elements of spatial organization. Also, they are best suited to learn patterns and features from the multiple input space of a new locale.

RNNs are designed for handling the sequences and can be applied to tasks that deal with time-series data or ordered data. They perform well in understanding temporal dependencies and relations for sequences.

To sum up, CNNs work well when dealing with spatial relations, which means that it works well when the data is still for instance images or spatial arrangements while RNNs concerns temporal sequences, thus it is suitable for dynamic data where the position or the context of the elements are of significance (Yan June Khoo, 2023).

7. USING DEEP LEARNING ARTIFICIAL NEURAL NETWORKS, SENTINEL-2 SATELLITE FOOTAGE HAS USED TO CAPTURE YELLOW RUST OF WHEAT IN ROOPNAGAR DISTRICT, PUNJAB

Punjab state's major cereal crop, wheat, is susceptible to a number of illnesses. Of them, yellow rust is the most common biotic stress and develops in chilly climates with favorable wind, precipitation, dew, and fog (Chen X. M.; 2005). The disease's primary symptom is development of yellow dust stripes on leaves. It decreases amount of green leaf area, due to which a drop in crop output. (J. G. Ellis et al., 2014). Fungal infection is one of the most devastating rust diseases that affect wheat crops, according to reports, and can result in large losses in crop output (Hovmøller M. S., et al., 20114). During the winter, when the climate is favorable for disease, in northern Indian region—which includes Punjab also—is seriously at risk of contracting it (Sandhu S. K., et al., 2016). The leaf spectra were measured using a field spectroradiometer by Zhang J. et al. (2014), and the rust signatures were produced by applying continuous wavelet analysis to the hyperspectral data. Normalized photochemical reflectance index (NPRI), according to (Wenjiang H., et al. 2005), can be used to diagnose rust based on hyperspectral data gathered from the field. In order to obtain in-field spectral images, Using a spectrograph positioned on a spray brush level (wavelength between 463 & 895 nm), Moshou D. et al. (2004). Crops that were diseased or not were categorized using disease detection algorithms that were created using neural networks. (Krishna G. et al. 2014), have also made use of the hyperspectral in-situ data that was gathered between 350 and 2500 nm in wavelengths. To determine extent of yellow rust in wheat crop, they created models utilizing multiple linear regression (MLR) and partial least squares (PLS). The coefficient of determination (R2) for each of models was 0.89 & 0.96, respectively. Ten popular narrow-band spectral indices were assessed by (Devadas R., et al., 2009) in order to distinguish rusts from individual wheat leaves. The visible and near-infrared portions of the electromagnetic spectrum's in-situ spectrometer observations served as the foundation for these indices. The crop affected by yellow rust had a robust reaction to every index. Using spectroradiometer data, Ashourloo D., et al. (2014) created two spectral disease markers to identify wheat leaf rust. Reflectance at wavelengths of 605, 695, & 455 nm was used to generate these indices. In both indices, there was an R2 of up to 0.94 between the estimated as well as observed values. These investigations demonstrate that the accuracy of proximal sensing methods in classifying yellow rust was higher than that of remote sensing methods. However, gathering the yellow rust spectra takes a significant amount of time and resources. Hyperspectral data is popular & yields reliable findings, but gathering, processing, and analyzing such datasets demands a significant amount of resources (time, computers, and hardware). Multispectral remote sensing data was utilized to identify yellow rust in very few investigations.

Sentinel-2 satellite data, which is publicly available, has revolutionized agriculture with its great geographical, spectral, and temporal resolution. A model for monitoring yellow rust has been proposed by (Zheng Q. et al., 2021), It is based on meteorological data, many two-stage vegetation indices, & Sentinel-2 multispectral images. Very few research have used Sentinel-2 data to identify yellow rust using machine learning approaches, despite the fact that few have used multispectral data to identify disease.

Algorithms for AI have revolutionized the field of crop diseases identification research. Because of their accuracy, DL techniques such as RNN, CNN, & ANN are becoming more & more popular. After reviewing the usage of DL of photos for plant diseases phenotyping, Singh A. K. et al. (2018) came to conclusion that deep learning algorithms require less pre-processing of data prior to modeling work. These algorithms work better, are more dependable, and are faster. In a similar vein, Saleem M. H., et al. (2019) claimed that deep learning offers a significant chance of improving the accuracy of agricultural disease identification from both proximal and remote sensor data. In 2020, Su J. et al. employed an unmanned aerial vehicle (UAV) to monitor wheat rust using multispectral pictures, and then applied convolutional deep learning algorithm 'U-Net' to this data. (Zhang X. et al., 2019) created a comparable method to detect rust, however they used a UAV to obtain hyperspectral photos. A novel method for automated crop disease diagnostics based on deep convolutional neural networks (DCNNs) has been proposed. Their model's total accuracy was 0.85. (Pryzant R., et al., 2017) used DL methods (such as ANN, CNN & RNN) in conjunction with field research and MODIS satellite data to monitor the wheat fungus. The model was developed using features that were automatically learned. There isn't a single study that used deep learning ANNs to evaluate Sentinel-2 photos for wheat yellow rust; instead, the majority of earlier studies employed deep learning CNN algorithms for this purpose. As a result, a study was designed to use Sentinel-2 & deep learning artificial neural networks to identify yellow rust disease of wheat in Rupanagar areas of Indian Punjab.

7.1. RESEARCH AREA

We chose the villages in Indian Punjab's northeastern region (the Rupanagar district) for our investigation. The district of Rupnagar is located in Punjab's Kandi belt and spans 1376 square kilometers, with latitudes of 30° 44' & 31° 26' N and longitudes of 76° 17' & 76° 44' E. It is located on eastern edge of Punjab & Haryana border to northeast & Himachal Pradesh to north.

7.2. DATA COLLECTION

On February 11, 2024, there were reports of severe yellow rust in wheat in Rupnagar region. Using Sentinel-2 data from https://apps.sentinel- hub.com/ eo-browser, the wheat crop's normalized difference vegetation index (NDVI) time series profile was evaluated for villages between December 2023 and March 2024. Around the same time, a decline in the NDVI readings was noted. To verify the presence of the disease infestation, a ground truth survey was also conducted. From the USGS Earth Explorer, Sentinel-2 satellite data (Level-2A product) for February 2024 was retrieved. The research work's approach or process flow is shown in Figure? Below-

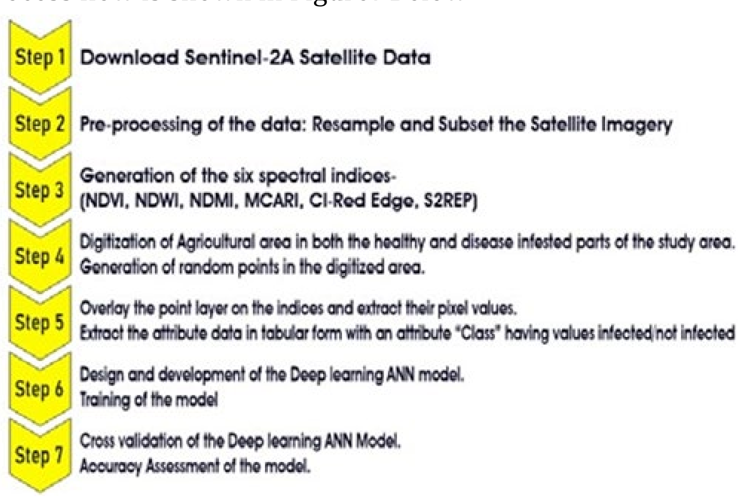

Figure 4

Source Research Made

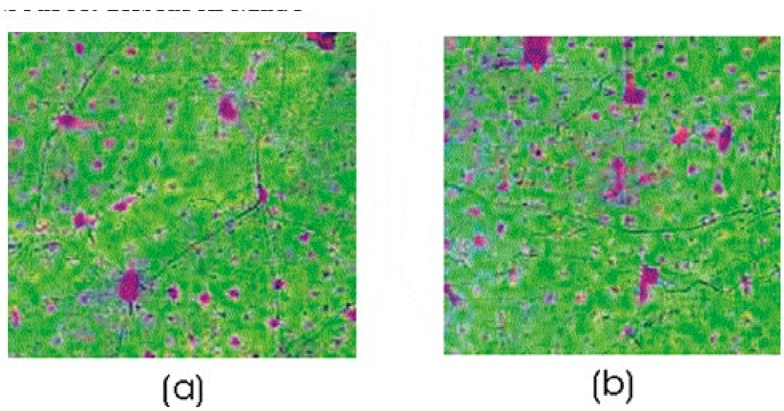

Figure 5 Sentinel-2 Image of Rupnagar District of dated (a) 11 Feb. 24 & (b) 28 Feb. 24

7.3. PRE-PROCESSING OF SATELLITE DATA

Using the SNAP 7.0 (Sentinel application program) tool, all Sentinel-2 bands were resampled to 10 m prior to data analysis. To create single raster stack with consistent pixel sizes from each of Sentinel bands, resampling was carried out. According to the study area's geographic boundaries, the data was subset. After being converted to GeoTIFF format, the composite dataset was analyzed using Quantum GIS (QGIS).

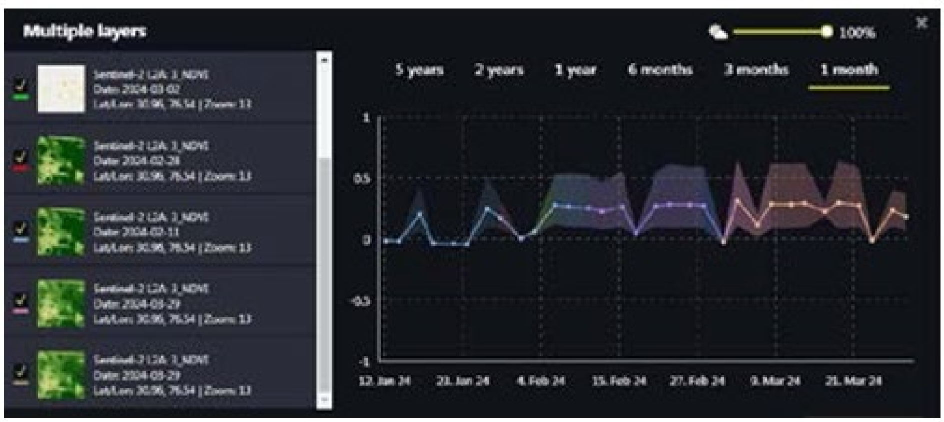

Figure 6 Statistical Information of Rupnagar District Satellite Images of Different Dates

7.4. CREATING SPECTRAL INDICES TO GET AGRICULTURAL INFORMATION

Table ? provides information on the six spectral indices that were created with QGIS's "Raster Calculator" tool: MCARI, NDVI, Cl-Red Edge, NDWI, S2REP & NDMI. Utilizing Normalized Difference Vegetation Index (NDVI), one can evaluate health of crops or plants. Its value was in the interval -1 to 1. Dense and healthy plants are indicated by higher NDVI readings. Plant relative chlorophyll abundance can be increased with use of Modified Chlorophyll Absorption in Reflectance Index (MCARI). It is susceptible to changes in leaf area index & amounts of chlorophyll. Neither background reflectance of soil nor that of non-photosynthetic materials has any effect on it. Cl-Red Edge, or chlorophyll red edge, is another marker of vegetative development. The red-edge position of Sentinel-2 (S2REP) is helpful in measuring the amount of chlorophyll. The moisture status of crops and soil is reflected in the normalized differential water index (NDWI). Higher plant water content and coating of plant percentage are correlated with higher NDWI readings. The normalized difference moisture index (NDMI) is used to calculate the water stress levels of crops or the amount of water present in the vegetation.

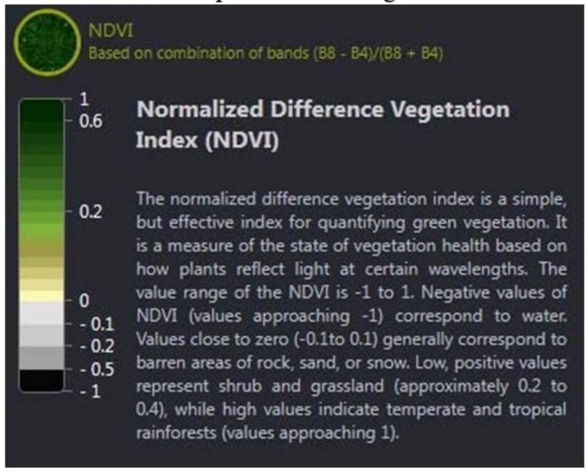

Figure 7 NDVI of Sentinel-2 Image

Table 5 The study employed spectral indicators to differentiate between wheat rust and yellowing rust

S.N	Index	Detail	Normal Formula	Formula with Sentinel- 2 bands
1	MCARI	Modified Chlorophyll Absorption in Reflectance Index	(700nm - 670nm) - 0.2 * (700nm - 550nm)) * (700nm /670nm)	((B05 - B04) - 0.2 * (B05 - B03)) * (B05 / B04)
2	NDVI	Normalized difference vegetation index	(NIR - RED) / (NIR + RED)	(B08 - B04) / (B08 + B04)
3	Cl-Red Edge	Chlorophyll red- edge	([760:800][690:720])p ow (−1)	$(B7/B5)^{(-1)}$
4	NDWI	Normalized Difference Water Index	(NIR - SWIR) / (NIR + SWIR)	(B08 - B011)/(B08 + B011)
5	S2REP	Sentinel-2 red-edge position	705 + 35 * ((((NIR + R)/2) − RE1)/(RE2 − RE1))	705 + 35 * ((((B08 + B4)/2) − B5)/(B6 − B5))
6	NDMI	Normalized Difference Moisture Index	(820nm - 1600nm) / (820nm + 1600nm)	(B08 - B11) / (B08 + B11)

Source Singh Harpinder et. al. (2023)

7.5. DATA PREPARATION FOR FEEDING THE ANN

The following are the procedures used to get the data ready for the ANN to receive it:

1) Sentinel-2 data for both research locations were used to identify the cropped area using QGIS. In the two digitally cropped portions (the study areas' infected & non- infected sections), 4000 points were generated at random in each.
2) The spectral indices were superimposed with spots. The vector points were used to extract the pixel values for each index. Ultimately, two vector datasets (shape files) were produced, each with seven attributes for each value of index pixel. For this effort, a QGIS plug-in called the Point Sampling Tool was utilized.
3) A tabular representation of the point layer's properties that were produced in the preceding step was extracted. An additional attribute called "Class" was introduced, with class having value 0 (non-infected) or 1 (infected). One file including data for 14 villages in Rupnagar district, had information about both affected & non- infested areas.

4) Training and testing datasets were created from the ultimate experimental data in an 80:20 ratio. Neural network was trained using training dataset, which allowed it to learn from input data & determine its weights & biases. By categorizing data that hasn't been seen before, test dataset was utilized to gauge network's performance. Additionally, it can support the network's calibrations in order to avoid overtraining.
5) To eliminate the effects of the attributes having huge values, data scaling was done in the end.

7.6. DESIGN AND DEVELOPMENT OF ANN MODELS

For this investigation, a backpropagation neural network (Figure 8) was created. There are six input neurons in the input layer of this network. The six index properties derived from satellite imagery correlate with each neuron. One neuron in the output layer indicates whether a point is infected with yellow rust (1) or not (0). To increase accuracy, the network was extended with two hidden layers. Although there is no set number of neurons to utilize in the hidden layers, we used a value of two (the average of sum of all input qualities + one). In both hidden layers, the rectified linear unit (ReLu) activation function was used to prevent negative values. The output layer employed sigmoid activation function due to its simplicity in derivatives & soft-switching capability. The network was compiled using the binary cross- entropy function & Adam optimizer. Weights can be effectively adjusted with this optimizer. Since challenge was binary classification, optimizer was combined with a binary cross-entropy function. Three batch sizes & an epoch value of 200 were employed in model fitting process. Model that was developed can be shown in Figures 8 (a) & 8(b). Using Jupyter notebooks, these models were implemented in Python programming language. Common Python libraries were also utilized, including NumPy, Pandas, & Keras. Eighty percent of experimental dataset was used for model training,

& remaining twenty percent was used for validation. To determine effectiveness of multispectral data for precisely detecting disease using DL models, accuracy, precision, recall, and F1 were computed.

One parameter used to assess classification models is accuracy. It is the percentage of accurate predictions model madeaccuracy answers the question of how accurate percentage of positive identifications was. Recall determines the percentage of true positives that were correctly detected. The F1-score is the weighted average of accuracy and recall. k-fold cross-validation sampling approach was also utilized to assess aforementioned models. Model was trained & validated using 10-fold cross-validation technique. Depending on the quantity of data, the entire dataset is randomly divided into 10 folds. Nine of these folds are used to fit the model as a training set, while the remaining set is used to validate the model. Until every 10-fold have used as test set & this process is repeated.

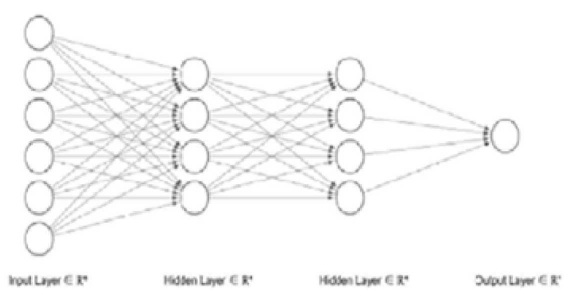

Figure 8 (a): ANN Layout

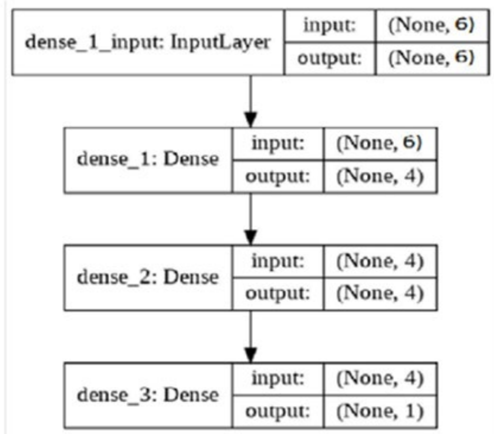

Figure 8(b): Structure of Model

7.7. RESULTS AND DISCUSSION

Spectral index response to yellow rust

Because the biochemical composition of healthy & diseased crops differs, spectral indices have used to identify & track crop illnesses. Following infestation, the yellow rust quickly depletes the plants' water, nutrients, and chlorophyll, changing the chlorophyll content of the leaves and reducing crop biomass. Sentinel-2 is distinct for tracking crop growth and illnesses because of its crimson edge band. The present study revealed that six spectral indices, namely MCARI, NDVI, Cl- Red, NDMI, S2REP, and NDWI, have effective in identifying yellow rust crop disease. These indices employ Red-edge, NIR, Red & Green bands, which correspond to degradation of crop tissues & chlorophyll, & subsequent shift in spectrum from visible to NIR band. Effects of a disease-induced decrease in crop & soil moisture were investigated using NDMI & NDWI.

Figs. 9 show how spectral indices responded to yellow rust, comparing average of each spectral index in healthy & non-healthy plants. Plants affected by disease showed lower values for MCARI, NDVI, Cl-Red & S2REP vegetation indices. Compared to healthy plants disease-infested plants had a 15% lower NDVI. MCARI was 1.25 times higher in healthy plants. Compared to healthy plants, sick plants had a 5% lower Cl-Red. Healthy plants had a 26% higher S2REP than ill plants. In plants with disease infestations, the NDMI & NDWI also decreased.

In order to maintain the same magnitude of spectral indices within -1 and +1, there was a greater difference in S2REP, MCARI, NDVI, NDMI, Cl- Red & NDWI for Rupnagar area, according to scaling of spectral indices for both disease-infested & healthy plants.

7.8. CLASSIFICATION OF HEALTHY AND DISEASED PLANTS

Using deep learning artificial neural networks (ANNs), the classification data of both healthy and ill plants revealed an accuracy & F1-score of 0.913 for Rupnagar. Table 6 contains Rupnagar studies' classification reports. For the Rupnagar area, 10-fold cross-validation values were 0.972 with a variance of 0.121. Based on spectral index values, the artificial neural network (ANN) developed in this work has trained to differentiate between data points from healthy & unhealthy plants. It presents a new angle by showing that wheat yellow rust might be successfully detected using multispectral satellite images and ANNs. When compared to conventional methods, the proposed methodology has several advantages. Firstly, it is less expensive for high spectral resolution and proximal data. Secondly, the multispectral imaging employed in this work is publicly available. (iii) A simple desktop PC without a GPU was used to train the ANN (tabular data) used in this study. However, training a CNN (picture data) is computationally quite costly. Traditional machine learning and statistical methods necessitate a laborious procedure for feature engineering, feature selection, and data pre-processing. On the other hand, deep learning requires relatively little; data can be sent into the network after a small amount of pre-processing. This study does have certain drawbacks, though. In Indian Punjab, yellow rust typically strikes during winter months when there is fog & cloud cover. During this time, it is challenging to obtain a satellite image free of clouds. Time interval between yellow rust's onset & fungicide's administration to suppress it is brief. It is consequently quite challenging to find a satellite image on an appropriate satellite pass date. Lastly, the model changes according to the season. The crop was affected by the yellow rust in January and February. The fact that the spectral indices vary over time is a primary factor in the lack of a worldwide model for wheat yellow rust.

Table 6: An overview of the ANN model's summary data for identifying wheat rust in the Rupnagar districts of Punjab, India

Wheat Plants	Precision	Recall	F1-score	Accuracy
Healthy	0.92	0.88	0.90	
With Yellow- Rust	0.89	0.93	0.91	0.91

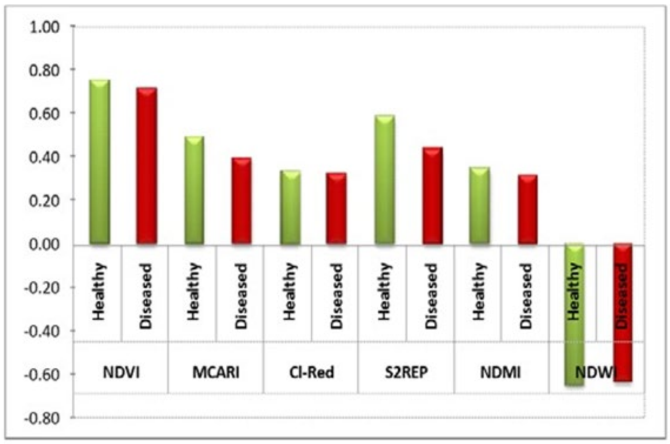

Figure 9: Spectral indices in the Rupnagar area's healthy & infected wheat plants

8. CONCLUSIONS OF THIS STUDY

The study's findings demonstrated that yellow rust disease of wheat crops retrieved from spectral indices produced by Sentinel-2 satellite data may be classified using deep learning artificial neural networks. The suggested model works well for localized monitoring of wheat yellow rust in crops; however, the data did not allow for the development of a global model. To create a regional/global model for disease monitoring, further work will be needed in the future. Nevertheless, meteorological factors (such as temperature, relative humidity, and sunshine hours) also have an impact on this illness; as a result, combining meteorological data with spectral indices may aid in the development of accurate crop disease forecasting models.

8.1. FUSION FRAMEWORK FOR CROP YIELD PREDICTION

Normally, the term ‘Fusion Framework for Crop Yield Prediction’ may mean a way that several source data systems and other predicting models may use to estimate crop yields. Here's a breakdown of what such a framework might entail:

Data Integration: Explained under the banner of the fusion framework, the approach aspires to obtain and compile a multitude of data sources bearing on crop yield prediction. Such datasets, may contain historical information such as; meteorological data (temperature, rainfall, humidity), soil data (type, water content, nutrient status), remote sensing data (vegetation indices, land use and land cover data), practices (crop rotation, planting dates, and irrigation) and; socio-economic data such as; prices and other relevant agricultural policies as well as demographic information of the intended farming area.

Feature Engineering: After the data is grouped, there is an application of what is referred to as feature engineering techniques that seek to arrive at predictors or features that might affect the yields in crops. This means development of variables that would enable analysts to glean useful information out of the collected raw data in terms of patterns and connections.

Model Selection and Fusion: The fusion framework include statistical, machine learning and possibly domain specific models to predict the crop yields. These models could be deep learning architectures such as convolutional neural networks, recurrent neural networks; machine learning techniques such as random forest, gradient boosting machines, support vector machines; or regression models such as linear regression, logistic regression. Arguably, they depend on the features of the data and the peculiarities of the task in question, specifically the conditions of the prediction.

Ensemble Techniques: The combination of individual classifier is a common strategy aimed at increasing the model's resistance to data transformations and enhancing the reliability of forecasts. This involves the use of multiple models' to arrive at a collective forecast that is more accurate than that of a single model. Some of the approaches used are bagging, boosting, and stacking among others that are under ensemble learning.

Uncertainty Estimation: Of course, one of the most important components of crop yield prediction is the estimation of forecasting error. Using uncertainties, Fusion framework employs the boot strapping technique, Monte Carlo simulations or Bayesian approximation in order to yield confidence intervals with probable distribution around the yields.

Model Evaluation and Validation: In this regard, it is possible to determine how well the fusion framework performs on historical data and this is done by employments of holds out validation techniques such as cross-validation and out of sample testing. To establish the effectiveness of the AI model in favourable accuracy and dependence, performance measurements are computed, which include mean absolute error, root mean square error or coefficient determination.

Integration with Decision Support Systems: Last, the fusion framework's predicted crop yields are fed into decision support tools that help farmers, government & other users in planning & managing crops, resources & risks as well as addressing issues of food insecurity.

Summarily, the framework for predicting crop yield through fusion gives a wide and innovative approach towards using various kinds of data for developing models that enhance the accuracy of crop output estimates for sustainable agriculture and food security.

Based on the primary studies of the present works, the integration of deep learning with time series analysis to forecast crop yield is discussed from satellite remote sensing data. The findings showed that the combination of such approaches improves the estimation of crop yield considerably higher compared to conventional approaches. Key findings include:

Enhanced Prediction Accuracy: The integration of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) attained a better perception of the spatial and temporal contexts within the sat merged data improving the yield forecast.

Robust Feature Extraction: Due to the high competence of these deep learning models, we proposed multi-layered and intricate patterns between the satellite imagery and crop yields that would not be captured by statistical models.

Temporal Dynamics Consideration: Introducing the effect of time series analysis enabled the model to capture the phenological phases of crops growth and be useful in deciding yield fluctuations in the proceedings of the growing season.

Scalability and Adaptability: The proposed approach can be easily generalized and applied to different crops and regions, thus, providing and example of applicability of this method to different problem of agricultural monitoring and decision- making.

Implications for Agricultural Management: The ability of this model to estimate yield will in a big way help farmers as well as those who formulate policies in the management of crops, distribution of resources and planning of food security.

Future work should include incorporating other predictant variables that are largely associated with weather conditions, type of soil and management practices among others. But, developing new configurations of deep learning coupled with transfer learning may help to achieve substantially higher predictive accuracy. The cone characterized by the encouraging result of this research opens up a vast opportunity for optimal utilization of deep learning fused with time series analysis in order to advance the efficiency of agricultural endeavours.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

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