Nigerian Journal of Technology (NIJOTECH)
Vol. 43, No. 4, December, 2024, pp.716 - 737
www.nijotech.com

Print ISSN: 0331-8443
Electronic ISSN: 2467-8821
https://doi.org/10.4314/njt.v43i4.12

PREDICTING WHEAT YIELD IN AGRICULTURAL INDUSTRY USING DEEP LEARNING TECHNIQUES: A REVIEW

AUTHORS:
P. Bari[1,*], and L. Ragha[2]

AFFILIATIONS:
[1]Terna Engineering College, Nerul, Navi Mumbai, India.
[1,2]Fr. C. Rodrigues Institute of Technology, Vashi, Navi Mumbai, India.

***CORRESPONDING AUTHOR:**
Email: poonam.bari@fcrit.ac.in

ARTICLE HISTORY:
Received: 07 May, 2024.
Revised: 05 November, 2024.
Accepted: 23 November, 2024.
Published: 31 December, 2024.

KEYWORDS:
Deep learning, Wheat, Disease, Vegetation index, Performance metric.

ARTICLE INCLUDES:
Peer review

DATA AVAILABILITY:
On request from author(s)

EDITORS:
Ozoemena Anthony Ani

FUNDING:
None

Abstract

In the post-pandemic future, technology in the agriculture industry can improve food sustainability while moderating the use of resources of nature in a variety of conditions. Robotic tools for agriculture have been developed for crop planting, nursing, clearing weeds, pest management, and harvesting. The key aspects of crop growth and innovative agricultural engineering help farmers maximize crop yield. In the present investigation, it has been found that deep learning (DL) algorithms are used to enhance the predictability of wheat crop yield. The assessment and forecasting of wheat crop yields can be done with precision and dependability using satellite imagery. The scientific investigations in this study to predict wheat crop yield considered distinct factors, including various vegetation indices with remotely sensed imaging, climate-related conditions, nutrients in the soil, wheat plant diseases, and water scheduling. This study expounds a variety of DL strategies for predicting wheat production and found that many publications make use of long short-term memory (LSTM), along with residual network (ResNet) and deep neural networks (DNN). The performance measures, commonly harnessed in publications, are highlighted in this study, including coefficient of determination (R^2), root mean square error (RMSE) and accuracy. This systematic evaluation of the literature on the wheat crop will open possibilities for future research for scholars.

1.0 INTRODUCTION

Agriculture is the process of cultivating crops and keeping livestock [1]. It contributes significantly to any nation's economic health via the cultivation of crops. It is regarded as the fundamental foundation of a nation and agricultural modernization occurs in tandem with technical advancement. Crops are essential for our well-being [2] and wheat crop is farmed on more land than any other crop in the world. Wheat is the world's second-largest crop in terms of grain acreage and overall production volume. In the marketing year 2021/22, international wheat yield totalled around 778 million metric tonnes [3]. Wheat is the second most important staple food after rice, consumed by 65 % of the Indian population [4], and its consumption is expected to rise further due to changes in eating habits. In India, wheat is largely consumed in the form of 'chapati' (flat bread), for which bread wheat occupies approximately 95 % of harvested land [4]. Durum wheat, which is most suited for creating macaroni, noodles, semolina, and pasta, occupies approximately 4 to 5 % of the area and is primarily farmed in Central and Peninsular India [4].

HOW TO CITE:
Bari, P., and Ragha, L. "Predicting Wheat Yield in Agricultural Industry using Deep Learning Techniques: A Review", *Nigerian Journal of Technology*, 2024; 43(4), pp. 716 – 737; *https://doi.org/10.4314/njt.v43i4.12*

The wheat crop productivity is the most significant aspect of ensuring food supply, as the global population grows dramatically. Researchers in agricultural domain from all across the world are seeking to identify techniques for increasing the yield of main food crops while minimizing the damage to ecosystems [5]. Agriculture yield is affected by a variety of elements, including weather conditions, details of insecticides, weeds, and nutrient availability. Aside of these considerations, precise knowledge regarding crop yield history is critical and a challenge for developing predictions and managing agricultural risk [6]. To forecast agricultural yield, mathematical approaches are typically used, which can be laborious and takes time. New developments in deep learning (DL) have emerged as a significant advancement in the field. Smart farming approach innovations provide obvious improvements for crop yield, cost reductions, and preservation of the environment [7]. DL is now being used by several companies, sectors, and organizations all over the world to boost productivity and improve processes. DL algorithms can derive information through facts in a manner that is similar to the way humans acquire knowledge which is why they are so successful. It has applications in practically every sector. DL, a further cutting-edge subset of machine learning (ML), processes data with multiple layers of algorithms to create perceptions or to mimic the cogitation process [5].

It is regularly attuned to understand spoken language and differentiate between objects visually. Every layer conveys data towards the one below it, with one layer's output providing another layer's input. The basic structure of each layer is a straightforward, homogeneous algorithm with an activation function. The first mathematical representation of a neural network was proposed by Mcculloch & Pitts [8]. This model's basic codified neuron serves as its basic unit. In order to simulate the intellectual process, they employed a set of mathematical formulas and approaches, titled ‘threshold logic’. A single-layer perceptron that can handle classification problems for linearly separable classes was developed by Rosenblatt [9]. The fundamentals of a continuous backpropagation model were created by Kelley [10]. Further exploring the backpropagation model, Dreyfus [11] presented a straightforward chain rule. Fukushima [12] presented a ‘Neocognitron’ neural network framework for the mechanism of visual pattern recognition. Rumelhart et al. [13] presented a novel learning technique that repeatedly adjusts the weights of the links in the network. The hidden layer accurately represents key features of the task domain as a result of weight modifications. It assisted in creating an internal framework suitable for a specific task domain. A backpropagation network was implemented by LeCun et al. [14] to recognize handwritten postal code digits provided by the United States Postal Service. The whole recognition process, from the character's normalized picture to the final categorization, is learned by a single network. Since then, a wide variety of architectures have been put forth in the scientific literature to address various tasks in various domains, ranging from the single-layer perceptron to the more recent neural network like LSTM, Recurrent Neural Network (RNN), ResNet, DNN, Visual Geometry Group Network (VGGNet), and U-Net, a Convolutional Neural Network (CNN) resembles the letter ‘U’ in the alphabet. Autoencoder, Generative Adversarial Network (GAN), AlexNet a CNN designed by Alex Krizhevsky, Gated Recurrent Unit (GRU), and many others have also been added.

Typically, everyone associate prediction with the weather, but this is no longer the case; it may now be applied in a variety of contexts. Pre denotes ‘before’, and diction is related to speaking. Thus, a prediction is a guess more about the upcoming event. It's an interesting observation, usually based on data or facts. Crop production prediction is one of the most difficult challenges in smart agriculture, with several models presented and proven so far. This problem requires the use of many datasets because crop output is affected by numerous factors such as soil, seed variety, weather, fertilizer use, and climate [15]. This suggests that crop yield prediction is an intricate operation with a sequence of rather complex steps. Though crop yield prediction methods now be giving predictions close to the actual yield, however, a more improved yield prediction is preferred [16]. Data mining, ML, and DL are fields of artificial intelligence that aid in predicting crop productivity based on datasets. The prediction is a two-step process in which the predictive model is built from traits and observations from prior or historical training datasets. In the second stage, the model's attainment is assessed using a validating dataset; the training and validation datasets are mutually exclusive.

A systematic literature review (SLR) is imparted to gain an impression of work done on the application of DL in predicting wheat crop yield. SLR identifies potential gaps in research on wheat crop yield prediction using DL technology and leading practitioners and scholars who seek to conduct additional research on this problem area. In SLR, all relevant readings are retrieved from the Scopus database, synthesized, and presented as solutions to research questions, such as different techniques to predict wheat production, what variables affect crop yield, and what assessment metrics were employed by the researcher. An SLR study opens up new views and assists new scholars in the subject in accepting the current state of the art.

Reviewing the literature is a common technique for thoroughly investigating numerous methods of the subject to be investigated. The farming sector is the primary focus of the article. Klompenburg et al. [17] conducted a review of numerous ML techniques to aid crop yield prediction research. They carried out research to extract and produce the algorithms and features used in crop yield prediction research. Muruganantham et al. [18] reviewed the practices of DL methodologies for crop yield extrapolation with remote sensing data. This article is the first comprehensive literature analysis focusing on the usage of DL techniques in the crop yield estimation challenge for wheat crops. The existing survey analyzes general crop productivity predictions, while this review specializes in wheat, which is widely consumed worldwide. This comprehensive literature review aids in understanding the adoption of DL algorithms related to agricultural yield prediction for wheat. This organized literature review will assist researchers in their analysis of wheat yield prediction using DL methods, as well as in studying the impact of vegetation indices and environmental factors on wheat growth. The goal of this review is to highlight the variety of research that exists with respect to agriculture for wheat yield prediction using DL techniques.

The article's sections are further organized as follows: Section 2 describes the review approach utilized in SLR. Section 3 discusses the DL techniques used in wheat crop yield prediction, the various factors that affect wheat crop yield, and the performance parameters used to evaluate the techniques. Section 4 concludes the study on wheat yields.

2.0 REVIEW METHODOLOGY

The review was carried out in accordance with the widely used research procedures established by Kitchenham et al. [19]. Thus, this study is divided into three stages plan-conduct-report review. During the planning stage, the research questions are defined, and taxonomy organization is defined, after identifying the necessity for review. During the conducting phase, databases for relevant research are identified. The database used in this exploration is Scopus database. Relevant research articles were identified, filtered, and thoroughly examined. In the third phase, all pertinent information from the selected articles is compiled and integrated in response to the study's objectives. The term ‘deep learning’ by itself will produce a large number of existing publications from different disciplines that are most likely unrelated to the review's objective and disrupt the search process. So, the search is restricted to the words ‘crop yield’, ‘wheat’ and ‘deep learning’ in the title, abstract and keywords from the Scopus database. The search on the Scopus database for writing this article was conducted on November 8, 2023. The Scopus database resulted in a total of 119 research articles. Thus, this study included 119 research articles, it did not include book chapters, conference papers, PhD and master's degree thesis, news items, or textbooks. Each study article was thoroughly examined, and material was gathered to represent the classification scheme from many perspectives.

2.1 Taxonomy Organization

After going through the work on wheat crop yield prediction research using DL techniques, the classification framework is mentioned below:

(1) Publication Year
(2) Journals and Publishers
(3) Authors in the study

The process presented by Bari and Karande [20] serves as a basis for the taxonomy organization paradigm. The publication year describes the trend in the wheat crop yield prediction research using DL techniques analysis over the years. The Journals and Publishers section focuses on where more related work has been published. The authors in the literature suggest the work incorporated into relevant research considering wheat crop yield prediction.

2.1.1 Publication year

The publication year describes the research direction during the last few years. The graph in Figure 1 depicts wheat crop yield prediction research that began in 2018 and has been steadily improving since then. A greater number of publications (39) are published in 2022.

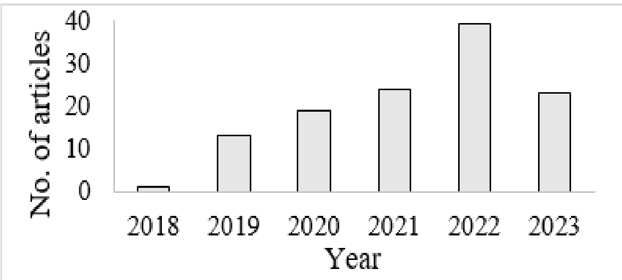


Figure 1: Articles with the publication year

2.1.2 Articles with journals and publishers

The journals and publishers' classification indicates where more work in the wheat crop yield prediction with DL topics has been published. The most publications are found in Remote Sensing (14.5%), Computers and Electronics in Agriculture (9.3%), Nongye Gongcheng Xuebao Transactions of the Chinese Society of Agricultural Engineering (8.3%), Frontiers in Plant Research (7.2%), and Plant Methodologies (6.25%). Agriculture Switzerland, Institute of Electrical and Electronics Engineers (IEEE) Journal of Selected Topics in Applied Earth Observations and Remote Sensing, and International Journal of Applied Earth Observation and Geoinformation and Sensors account for 4.16% of total studied articles, while International Journal of Applied Earth Observation and Geoinformation and Sensors account for 3.12%. Each journal has two articles: International Journal of Remote Sensing, Neural Computing and Applications; Neurocomputing, Plants, and Precision Agriculture. Journals with only one research publication are not mentioned due to space constraints. The number of articles published in journals is shown in Table 1.

Table 1: Summary of journal names and related articles count from Scopus database

Name of Journal	No. of articles
Remote Sensing	14
Computers and Electronics in Agriculture	12
Nongye Gongcheng Xuebao Transactions of The Chinese Society of Agricultural Engineering	9
Frontiers in Plant Science	8
Plant Methods	6
IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	5
Sensors	5
Agriculture Switzerland	4
International Journal of Applied Earth Observation and Geoinformation	4
Ecological Informatics	2
IEEE Access	2
International Journal of Remote Sensing	2
Neural Computing and Applications	2
Neurocomputing	2
Plant Pathology	2
Plant Phenomics	2
Plants	2
Precision Agriculture	2

Considering the publishers, MDPI supplied the most research papers (26%) on wheat crop yield estimates with DL algorithms, followed by Elsevier (22%), Chinese Society of Agricultural Engineering, Frontiers Media and Springer (7%) each, IEEE (6%), BioMed Central (BMC) Ltd (5%), and Taylor & Francis Ltd (3%). Other publishers contributed a total of 18% to the study. The literature review from aforementioned publishers reveals a wide range of work research shown in Figure 2.

2.1.3 Authors in the study

This study identifies the authors who took an active role in and contributed to the latest publication of the research papers. Overall, 119 research publications on the work were written by 256 researchers. From 119 research publications, all authors—both the primary author and co-authors—were taken into consideration. The top 23 authors having three or more scientific papers who have all contributed to the publication and shown their work for predicting wheat crop yield, are given in Table 2. They appear to be the authors who contributed the most to the publication of the scientific work. Due to space restrictions, the remaining 233 authors, who each produced one or two research publications, are not included here.

Table 2: Authors in study with article counts

Name of Author	Count	Name of Author	Count	Name of Author	Count
Haq, I.U.	4	Di, L.	3	Luo, H.	3
Mumtaz, R.	4	Hafeez, M.	3	Ma, J.	3
Shafi, U.	4	He, X.	3	Marwaha, S.	3
Tansey, K.	4	Hu, G.	3	Qiao, M.	3
Tian, H.	4	Huang, J.	3	Sun, Z.	3
Wang, P.	4	Jain, R.	3	Tian, Z.	3
Zaidi, S.M.H.	4	Liang, D.	3	Zhang, S.	3
Arora, A.	3	Liu, J.	3		

3.0 DISCUSSION

This paper serves as a comprehensive foundation for presenting the research of DL methodologies utilized in wheat crop yield prediction. An attempt was made to collect information from all relevant research articles. It is envisioned that the proposed methodology, concepts, grouping considerations, and interpretation of the study will be an efficient way for research scholars and practitioners involved in wheat crop yield prediction using DL techniques' study, and will help to encourage advanced study in this field. This section covers techniques required to demonstrate an understanding of how to anticipate wheat yield, factors that are used to explain how they influence wheat yield prediction and evaluation metrics that aid in determining the quality of approaches used to estimate the yield of wheat.

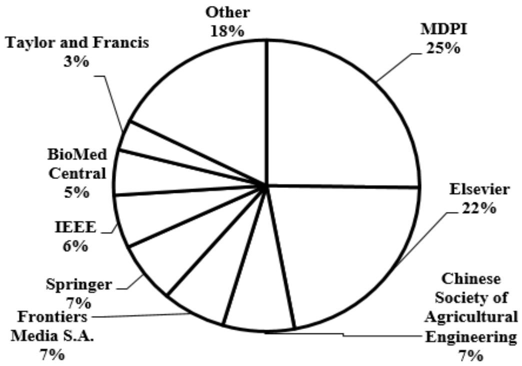


Figure 2: Publishers in research

3.1 Deep Learning Techniques used in Wheat Crop Yield Prediction

To achieve the solution goal, many DL algorithms for predicting wheat crop yield could be used. Although various algorithms could be utilized, there is no such thing as the optimum algorithm for every situation. Since it is subject to diverse features, a method that is acceptable for solving one problem may not apply to another. After an investigation, a few of the primary solution strategies are recognized and illustrated in Figure 3.

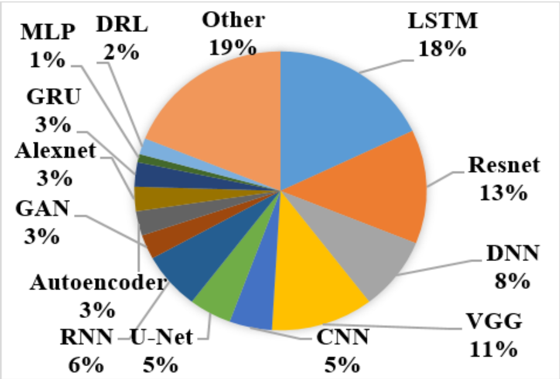


Figure 3: Solution strategies to predict wheat yield

3.1.1 Multilayer perceptron

Our brain is made up of many neurons that interact with one another to allow us to do complicated processing and learning as needed. Thus, an artificial model can be created; the most basic artificial model for DL is a Multilayer Perceptron (MLP) known as a feedforward network [21]. The feedforward network maps output to input and learns the parameters that produce the best function optimization. MLP's basic structure comprises a densely connected network comprising input, output, and several hidden layers. All of these layers are linked together through a dense network of neurons, each with its own weight [21]. Figure 4 shows the basic MLP with one input layer, one output layer and two hidden layers.

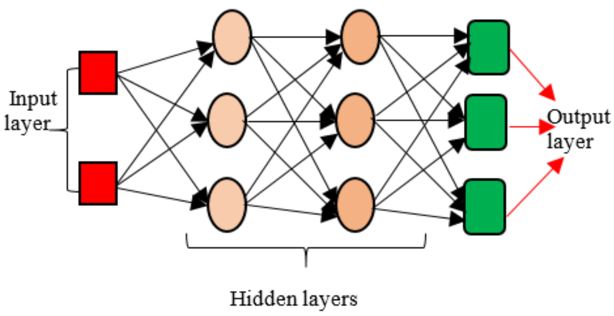


Figure 4: The basic structure of MLP

3.1.2 Convolutional neural network

A CNN is a form of artificial neural network in which the hidden layers are made up of convolutional, pooling, flattened, and fully connected dense layers [22]. CNN continuously conducts the convolution operation together using an input of a given width and length in each convolutional layer using kernels and filters. The filter travels over the input for the same window size, and CNN computes the weighted sum, which creates the feature map. Every convolutional procedure learns the coefficient of the 'kernel' or filter, which is similar to MLP neurons [22]. Figure 5 presents the fundamental structure of CNN.

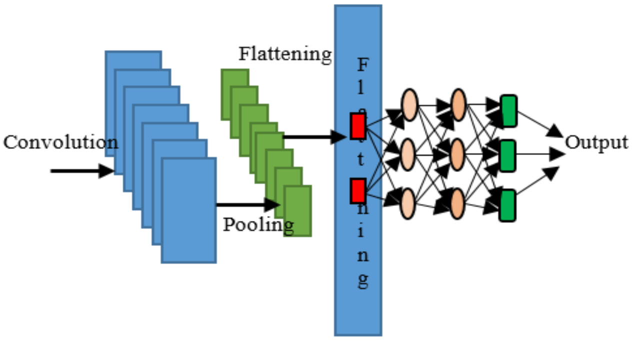


Figure 5: Fundamental structure of CNN

3.1.2a LeNet

CNN was first introduced by Yann LeCun in 1989 under the name LeCun network (LeNet). LeNet is a CNN which helps in the recognition of digits [23]. A full convolutional layer is made up of a number of feature maps, allowing for the extraction of many features at every location. LeNet comprises seven layers, the input is a 32 x 32-pixel image of characters. The layers and their description are given below in Table 3. Figure 6 [23] depicts the architecture of LeNet CNN, with Ci, Si, and Fi representing convolution, subsampling, and fully connected layer, respectively.

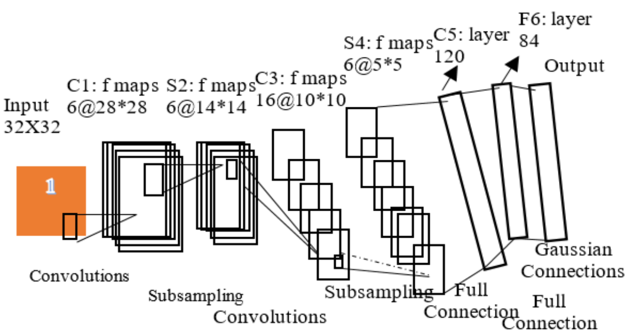


Figure 6: LeNet architecture for recognition of digits

Table 3: Layers in LeNet

Layer	Layer name	Number / Size of feature map	Trainable parameter	Trainable Connections
1	Convolution	6/28 x 28	156	122304

https://doi.org/10.4314/njt.v43i4.12

2	Subsampling	6 /14 x 14	12	5880
3	Convolution	16/10 x 10	1516	156000
4	Subsampling	16/5 x 5	32	2000
5	Convolution	120/1 x 1		48120
6	Fully connected	84 units		10 164
7	Output	10 units		

3.1.2b VGGNet
CNN, referred to as VGGNet is used for largescale image recognition, and it was created by the Visual Geometry Group at the Department of Engineering Science, University of Oxford by Karen & Zisserman [24]. They have measured with hidden layers at a depth of 16–19. In order to seize the idea of right/left, up/down, and centre, an architecture with very trivial (3 X 3) convolution filters was used. Bari and Ragha [25] employed VGG to identify pests and subsequently recommended necessary pesticides, enabling farmers in implementing technology to boost yield. Framework for VGG16 used by authors [25] is shown in Figure 7.

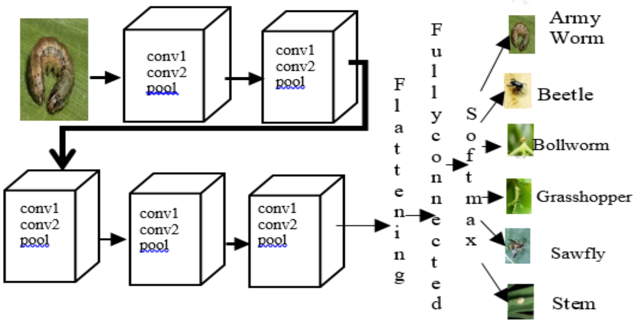


Figure 7: Framework for VGG16

3.1.2c Google Network (GoogLeNet)
Researchers at Google presented a GoogLeNet CNN in 2014. Szegedy et al. [26] developed the network with usability and computing effectiveness as their goals, such that implementation can be used on personal computers, even ones with minimal processing power, especially those with small memory footprints. The network is 22 layers deep when counting only layers. The network consists of 22 hidden layers. There are around 100 layers employed in the network's creation overall. Rectified linear activation is used in GoogLeNet. Using transfer learning, the well-known deep CNN model GoogLeNet has the best ability to classify with an error rate of 6.67%. [27].

3.1.2d ResNet
ResNet, which is short for Residual Network, introduced by He et al. [28] is a different type of neural network. Generally, beneficial to unravel complex problems, one can pile up a few more layers in the neural network resulting in enhanced performance and accuracy. The idea behind adding additional layers is that these layers progressively learn more complex features. The direct connection that deep ResNet architecture establishes for dispersing information throughout the network demonstrates its high performance [28]. In addition to the typical convolution layers, ResNet also incorporates skip connections that aid in the network's ability to acquire global features. In order to add the input parameter *x* to the final output following the weight layers, the skip connection is linked. By removing connections that are not necessary, the network achieves optimal tuning and can train networks more rapidly. Without employing this skip link, the input *x* gets multiplied by the layer weights, then an additional bias term is plugged in, and finally, this term is passed by the activation function to produce the output [28]. ResNet solves the problem of vanishing gradient in deep neural networks using skip connection by permitting this alternating shortcut path through which the gradient will flow through. Figure 8 represents the residual connection in ResNet50 [28].

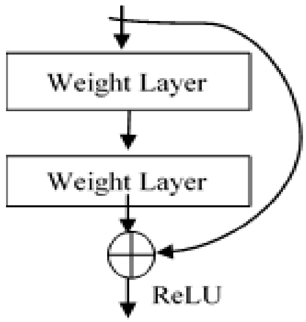


Figure 8: Residual connection in ResNet50

3.1.2e U-Net
A deep convolution network was developed by Ronneberger et al. [29] for the segmentation of biological images. To create more images for training the model, they use data augmentation. The architecture includes a contracting path for storing context and a symmetric expanding path to allow precise localization. CNN often need more images to train the model, however, they illustrated that a network may be trained from beginning to end with just a small number of images [29]. The U-Net's structure contains down and up sampling, and the entire network resembles the letter 'U'. The trained U-net model can be utilized to rapidly segment the image, automatically acquire the necessary features, execute from beginning to terminate learning and elude the impacts caused by incomplete, insufficient and artificial features representativeness that happen with the random forest [30].

3.1.3 Recurrent Neural Network (RNN)

A pile of recurrently associated hidden layers is supplied as an input vector sequence through weighted connections in order to calculate the hidden vector sequences first, and then the output vector sequence [31]. RNN is a DNN with short-term memory competences. To parameterize a predictive distribution over the potential following inputs, each output vector is needed. Every input sequence begins with a null vector, which has all of its entries set to zero. As a result, the network always outputs a prediction for the following input, which is the first genuine input, with no prior knowledge [31]. Every piece of information flowing either vertically or horizontally through the computing graph will be affected by numerous subsequent weight matrices and nonlinearrities, indicating that the network is 'deep' in both space and time [31]. RNNs are frequently used for applications including speech recognition, language modelling, and the creation of natural language. Figure 9 [31] shows the architecture of RNN.

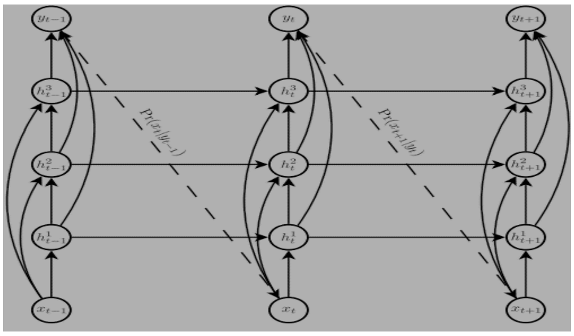


Figure 9: Deep recurrent neural network prediction architecture [31]

3.1.4 LSTM

LSTM is a unique type of RNN, because of its recursive structure, gating mechanism, and processing of sequential data in addition to its control over information input and exit into and out of cells. With outstanding findings, LSTM was employed across many research to estimate wheat crop yield. The LSTM is frequently chosen for processing, classification and prediction contingent on time series data since it contains feedback connections and can accept input series of any size. LSTM not only seizes patterns in the data but also shows the interdependence of the time series data [32]. A neuron within a cyclic neural network receives input from other neurons as well as from itself, creating a structure of networks with circles. Compared with feedforward neural networks, RNNs are more in line with the architecture of biological neural networks. RNNs are composed of a series of neural network repeating modules. The backpropagation algorithm can gradually learn the parameters of RNN [32]. The error information is transmitted in reverse chronological order using the backpropagation process. Gradient explosion and extinction are issues that arise with reasonably long input sequences. The cyclic neural network has undergone several changes in order to address this issue. The introduction of a gating mechanism is the most efficient way to improve the cyclic neural network. A simple cyclic neural network can experience gradient explosion or even vanish, but the LSTM is a variation of the cyclic neural network that can handle these issues well [32].

A gating system is employed by the LSTM network to regulate the direction of transmitting data. By carefully controlling information removal and addition via gates, the LSTM may change the cell state. The LSTM cell with gates is shown in Figure 10. The input gate (i_t), forget gate (f_t), and output gate (o_t) are the three 'gates' used in LSTM. f_t determines how much data must be erased to regulate the internal state c_t-1; i_t determines the candidate status c_t at the instant and what amount of data must be preserved; the amount of data from the internal state c_t that must currently be output to the exterior state h_t is controlled by o_t [32]. The beauty of LSTM is that the input, forgetting, and output thresholds may all be raised in order to change the weight of the self-loop. As a result, when the model parameters remain unchanged, the integration scale at various periods can be altered continuously, eliminating the issue of gradient expansion or vanishing [32].

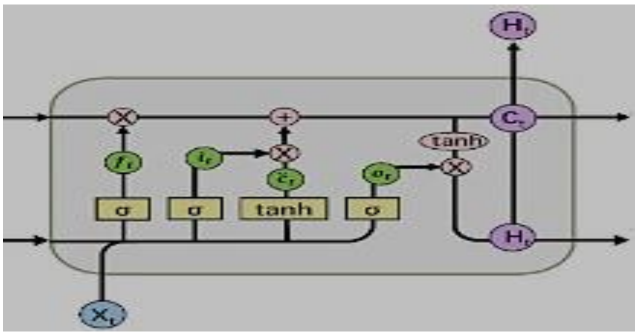


Figure 10: The cell structure of the LSTM network [32]

3.2 Wheat Crop Yield Prediction with Different Factors

The advancements in data science, sensor technology, and ML and DL have boosted hopes for farmers to develop more efficient and effective ways to improve production. In multiple areas of agriculture, including crop yield prediction and assessing the effects of various meteorological conditions and agricultural practises on total yields of crops, a number of ML and

DL models have already been examined. Researchers have explored the following elements that affect wheat yields.

3.2.1 Vegetation index (VI)

Various vegetation indicators represent various components regarding crop development and state of health. Integrating many indices is capable of offering a more complete knowledge of agricultural conditions. The steps shown in Figure 11 can be used to predict wheat crop yield using various vegetation indices.

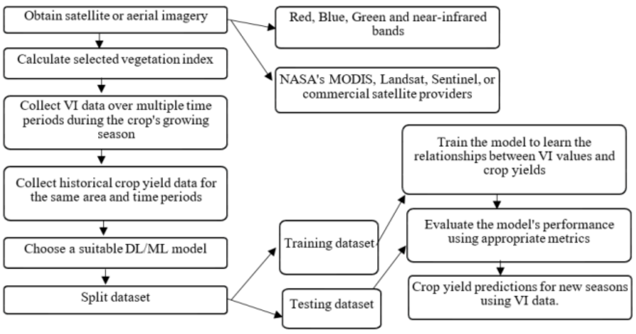


Figure 11: The general process for predicting wheat crop yield using VI

The first phase is gathering information from numerous sources, such as NASA's MODerate-resolution Image Spectroradiometer (MODIS), Landsat, Sentinel, or private satellite providers. The vegetation index (VI), which is calculated using satellite or aerial images with various colour bands and near-infrared wavelengths, yields a value between -1 and 1, with a higher score showing healthier vegetation. Now, during the crop's period of development, VI data is collected over several time frames. This generates a time-series dataset that shows the development and well-being of the crop through time. Later, past crop yield data are gathered for the same region and time period. For model training and validation, this data acts as the source of truth to create training and test sets from the dataset. This aids in assessing how well the model performs on unobserved data. The next step is to identify an appropriate ML/DL model, then train the chosen model with the help of the VI time-series data and the wheat crop yield data. The model gains the ability to forecast crop output using VI. Utilizing the right performance indicators, the models may be evaluated. The trained model is prepared to forecast wheat crop yields for upcoming seasons utilizing VI data.

After an investigation, a few of the vegetation indices are recognized and listed below:

3.2.1a Normalized Difference Vegetation Index (NDVI)

NDVI is a method of remotely sensed data applied to analyze the state of health and amounts of vegetation. It is derived by subtracting the total of a crop's visual red (Red) from the near-infrared (NIR) coefficient of reflection and then dividing that difference by the total of the coefficient of reflection given by Equation (1) [33].

$$NDVI = \frac{NIR-Red}{NIR+Red} \quad (1)$$

Jamali et al. [34] considered NDVI and perpendicular vegetation index (PVI) with sentinel-2 data to estimate wheat leaf metrics such as leaf weight, dry leaf weight, and leaf area index (LAI). They discovered that the NDVI helped in the prediction of wheat leaf metrics more effectively than the PVI. NDVI was employed as one of the primary elements in predicting the productivity of plants and it was discovered that NDVI-based systems are going to become significantly essential in the agriculture domain [35]. Xie and Huang [36] applied the LSTM model to detect the winter wheat cultivation locations in Henan Province using a time series of MODIS NDVI. Evans & Shen [37] studied the correlations between phenological and seasonal climatic parameters and yield. They discovered that the geographical and time-related variations in wheat yield were potentially explained by NDVI during the period of cultivation. X. Wang et al. [38] used NDVI as an input together with climatic and soil information for predicting winter-time wheat yield one month before harvesting at the level of the country in China's primary growing area.

Wolanin et al. [39] used NDVI and minimum temperature as parameters and a deep neural network for predicting wheat yield. They discovered that these two variables alone did not aid in properly forecasting yield, thus they incorporated more variables in wheat yield prediction. NDVI is utilized to detect images that are cropped at the given point of observation in order to select suitable Landsat images for classification [40]. In order to improve the precision of state-wide wheat production predictions in Henan Province, China, Xie and Huang [36] employed DL methods by integrating a crop growth model and a time series of data collected via satellite. The LSTM model generated a better prediction of wheat yields than the one dimensional (1D) CNN and random forest models, having greater R^2 values and lesser RMSE and mean relative error (MRE) values. Moghimi et al. [41] created a sensor-based system for wheat yield phenotyping. They could effectively predict the yield of the assessed field with $R^2 = 0.41$ and NRMSE = 0.14 along with sub field with $R^2 = 0.79$ and NRMSE = 0.24. Nevavuori et al. [42] concentrated on a spatial level that allowed them to estimate intra-field yield distribution in the setting of particular farm crop management. The results show that CNN models may generate reasonably accurate yield predictions based on RGB images. They discovered that the CNN model appeared to do better for RGB images than with NDVI images.

3.2.1b Enhanced Vegetation Index (EVI)

The Enhanced Vegetation Index (EVI), like NDVI, is a method commonly employed to measure the health of trees and plants calculated by Equation (2). Still, EVI accommodates some climatic variables and canopy background noise, and it is more susceptible in densely vegetated areas.

$$EVI = Gain * \frac{NIR - Red}{NIR + (coeff_1 * Red - coeff_2 * Blue) + L_{adjust}} \quad (2)$$

where Gain is a gain factor ($Gain = 2.5$), and $coeff_1$ and $coeff_2$ are aerosol resistive factor coefficients that use the 500-m blue channel (Blue) of MODIS to account for aerosol contributions in the red channel ($coeff_1 = 6.0$ and $coeff_2 = 7.5$), and $L_{adjust} = 1$ is a canopy background correction factor [33].

The EVI was created to eliminate the atmospheric and canopy background disturbances that typically harm the NDVI [33] and improve the ability to detect the green vegetation indicator at higher amounts of green biomass than the classic NDVI metric. Y. Wang et al. [43] employed EVI and other vegetation indices, and EVI was identified as an important component in predicting agricultural productivity. According to Tanabe et al. [44], the CNN model for unmanned aerial vehicle-based multispectral imaging proved reliable predictions of yield strategy for winter wheat. They observed that multiple linear regression depending on the multi-temporal EVI declined compared to the CNN model contingent on a single season.

3.2.1c Green Chlorophyll Index (GCI)

GCI may capture crop growth-related canopy chlorophyll amount and light extraction effectiveness. GCI was taken into account as one of the parameters by Y. Wang et al. [43] to predict the crop yield. Equation (3) can be used to calculate GCI.

$$GCI = \frac{NIR}{Green} - 1 \quad (3)$$

where Green represents the coefficient of reflection for the green channel.

3.2.1d Modified Chlorophyll Absorption Ratio Index (MCARI)

The MCARI is affected by the proportion of chlorophyll in the leaf and the ground coefficient of reflection [45]. In general, high MCARI readings suggest a poor proportion of chlorophyll in the leaf. The effect of soil signal restricts the efficacy of MCARI in forecasting poor chlorophyll proportion. As a result, MCARI should be evaluated in conjunction with NDVI or LAI [45]. Tesfaye et al. [45] chose MCARI as one of the parameters, along with others, that influenced wheat yield prediction. It is calculated with Equation (4).

$$MCARI = \left((NIR - Red) - 0.2 * (NIR - Green)\right) * \frac{NIR}{Red} \quad (4)$$

3.2.1e Leaf Area Index (LAI)

The leaf is a vital indicator for determining crop growth. Detecting and tracking leaf metrics can help in crop yield monitoring and projections, which is critical for ensuring adequate food supply. LAI is a key measure for characterising conditions for cultivating crops and estimating crop output, and it additionally contributes to an integral part of vegetative activities including photosynthesis and transpiration [34].

J. Wang et al. [32] fed the LAI into a wheat crop forecasting algorithm. They investigated the influence of LAI time-series data on the approximation findings for LSTM traits. The findings showed that when LSTM is used to estimate yield, the results are more accurate than when using more conventional ML techniques, with $R^2 = 0.87$. The calculated LAI from the CNN system was employed as an input parameter for predicting winter wheat yield, and the authors demonstrated that the calculated LAI and observed yields correlated significantly [46]. LAI can accurately indicate the development state of winter wheat. LAI at the four developmental phases of winter wheat cultivation, as well as county meteorological data, were utilized as inputs to a generative adversarial network-based data augmentation approach for improving the efficiency of yield estimation [47]. Tian et al [48] revealed that one of the most significant factors impacting yields in wheat crop growth was LAI at the heading filling and milk maturity phase. To estimate country level winter wheat production, Di et al. [49] suggested a Bayesian optimization-LSTM approach which incorporates meteorological, satellite imagery, and LAI with phenological variables.

When using Sentinel-2 LAI time series as data input, Xie [50] demonstrated that the LSTM model outperformed the RF technique for estimating wheat

https://doi.org/10.4314/njt.v43i4.12

production. The author discussed the combination of crop growth models, remotely sensed, and the LSTM approach to provide a more trustworthy crop yield projections across wide areas. The LAI was utilized to train and test the different DL and ML models and observed that models gained significant data from multiple LAI curves for wheat yield forecasts [36]. Jie Wang et al. [51] illustrated the ensemble CNN-GRU model for reckoning region-level winter wheat yields using remotely detected parameters, LAI, vegetation temperature condition index, and a fraction of photosynthetically active radiation and proved that the ensemble DL model outperformed with $R^2 = 0.64$.

3.2.2 Spike and spikelet count

It requires an extensive amount of time and effort to count the spikes on a plant or in a certain area by hand. As a quick substitute, environmentally friendly spike identification and counting, using imagery analysis are required. Counting the total amount of spikes is a crucial step in determining the yield of the wheat crop since it helps to quantify the quantity of grains produced per unit area. For phenology-based input control for agricultural production and evaluating crop output, spike identification and tracking are crucial. Many researchers have recently focused on using artificial intelligence to identify and locate things like the spikes and spikelets in wheat plants. Colour component selection and image analysis approaches, together with DL, were presented to identify and quantify wheat spikelets in colour photographs. CNN successfully estimates the quantity of wheat spikelets, which enhances wheat spikelet counting effectiveness and adds to the understanding of wheat spike development features [52].

Alkhudaydi and De La lglesia [53] developed spike count, a fully convolutional network that uses a density estimation technique to count spikelets for predicting wheat yield. Misra et al. [54] implemented a method for measuring the amount of wheat plant spikes in digital photographs by segmenting the image for spike section recognition. The analyzed DL network was able to identify spikes with a success rate of 99.91%, while spike counting had an accuracy of 95% on average. A DL CNN model was developed by Sadeghi-Tehran et al. [55] for measuring the amount of spikes in photos from farm areas and determining the amount of spikelets per square metre. The UNet approach was used by Zaji et al. [56] to create a new model using previously learned frameworks including VGG16-UNet, ResNet34-UNet, and ResNet50-UNet. In order to predict wheat yield, J. Chen et al. [57] introduced an Android application that used to count the number of spikes per unit area. They used photographs of a wheat farm and advanced spike tracking per unit area to predict wheat crop yield, avoiding a requirement for an in-field wireless internet or phone network. Hasan et al. [58] presented an R-CNN model to identify and quantify spikes in photos of a complicated wheat farm. They examined 20 photos totalling 1570 spikes and found that the DL model's F1 score and accuracy are 0.95 and 93.4%, respectively.

3.2.3 Climate and soil

Evans and Shen [37] investigated weather phenological and seasonal climate factors extracted from spatially weighted growth curve estimates wheat production on Landsat NDVI. They identified the best models by combining phenological and seasonal climatic indicators: DL MLP and support vector regression models were developed and the MLP model was the best because, with a sufficient quantity of cloud-free images, it is easier to apply and also produces more results over time. Di et al. [49] suggested BO-LSTM based on Bayesian optimization (BO) that combines crop phenology, climatic, and remotely sensed information to estimate country level winter wheat yields. When compared to linear regression, the BO-LSTM model exhibited the best yield prediction performance with RMSE = 177.84 kg/ha, $R^2 = 0.82$. Fei et al. [59] revealed that the ensemble feature selection strategy increased grain yield prediction from hyperspectral data and also assisted wheat breeders in making earlier decisions. Chandel et al. [60] discovered that DL models outperformed ML models for non-stressed and stressed crop categorization by considering parameters like temperature, water and soil moisture content. Of the function approximation-based techniques evaluated DL-LSTM had the highest accuracy (96.7%).

ResNet50 had the highest accuracy of the feature extraction-based techniques, with 96.9% and 98.4% with RGB and thermal images input, respectively. Adesanya and Yinka-Banjo [61] created a mobile application for small landowners to identify nitrogen deficit in plants. In order to forecast wheat yield at the county and field levels from 2011 to 2015, Cao et al. [62] utilized ML and DL models. They employed a dataset comprising several characteristics linked to soil, and weather-associated factors and could predict wheat crop productivity with good accuracy. By taking into account weather datasets containing humidity, temperature, rainfall, wind direction, and evaporation characteristics, a DL-based RNN and RNN-LSTM model was used to estimate wheat crop output in northern Punjab of India. It was found that the RNN-LSTM model performed well [5]. In order to predict wheat crop production, Kaur et al. [63] constructed the LSTM model by taking into account a number of variables linked to weather and soil data. In order to anticipate the production of soft wheat in Germany, Paudel et al. [64] executed LSTM approaches taking into account the soil's ability to retain water, biomass features, moisture levels, and temperature. They discovered that DL is capable of learning attributes and generating accurate crop yield predictions. Huang et al. [65] used authorized province-level data of past winter wheat yields to train and test the DL model. They explored non-linear connections between winter wheat yield and predictor variables derived from multiple sources, including remote sensing, weather, and soil parameters.

Tripathi et al. [66] predicted wheat yield based on remote sensing information Sentinel-1 and Sentinel-2 of Punjab, India, by taking parameters like moisture, salinity, and organic carbon of soil into consideration. The soil health-based DL MLP model performed better over the least squares regressor in crop yield estimation, with $R^2 = 0.723$ and 0.684 in the training and testing stages, respectively. According to the methods put forward by Kumar & Pandey [67], the yield of wheat can be estimated by taking into account information on crop production, water from the rain, and the state of the soil. This is done by using a hybrid deep capsule autoencoder and a softmax regression. Daniel et al. [68] created a system that assisted in crop selection and price prediction in order to improve farmers' crop selection with a high benefit. They used the soil test report to calculate the amount of fertilizer required. Fajardo and Whelan [69] used CNN techniques to predict agricultural yields using a dataset of soil parameters. J. Sun et al. [70] introduced a DL model that extracts spatial and temporal characteristics by combining RNN and CNN. Time-series satellite data and soil information are used as inputs, and the model produces crop yield. They tested the model in the Corn Belt of the United States and used it to forecast county-level yield from 2013 to 2016. The outcomes demonstrated the potency of the combined DL approaches.

3.2.4 Disease

Wheat is heavily damaged by different diseases because of increasing seasonal variance. Wheat diseases can severely reduce yield and pose a major danger to the world's food supply. Infectious wheat plants frequently exhibit symptoms that skilled agricultural specialists use to diagnose the type of disease ailing the plant. The traditional visual method of diagnosis, on the other hand, is time-consuming and difficult, necessitating highly educated experts who are intrinsically constrained in their ability to cover huge areas. As a result, researchers investigated diseases and used DL to automate health diagnoses for wheat plants. Li et al. [71] suggested a viable aphid preventive approach. Experimental findings on the dataset utilized with CNN reached aphid counting capability of 10.22 mean absolute error and 12.24 mean squared error. Nigam et al. [72] proposed a CNN approach for detecting healthier as well as yellow rust-infected wheat leaves. They recorded 97.3% accuracy in testing and 98.42% accuracy in training. J. Jiang et al. [73] used field images to detect wheat leaf diseases like powdery mildew, leaf rust, and stripe rust. They developed different deep CNNs for crop disease diagnosis and reached an identification accuracy of 92.5% on the test dataset with the Inception-v3 CNN model. DL network used by Long et al. [74] to identify and categorize wheat photos as having healthy plants or having diseases like brown, yellow rust, mildew, or septoria leaf spot. The results demonstrated the effectiveness of DL networks for recognizing diseases and categorization.

3.2.5 Water

Due to population growth and human activity, water shortage has become a major concern. Crop water stress monitoring in real-time can help with precision irrigation control and reduce yield loss due to water loss. Jia et al. [75] investigated DL and the hybrid fuzzy uncertainty optimization method to forecast agricultural yield per unit area and a benefit planning model for water management. The integration of the two models, via the crop-water production function, can efficiently deal with crop plantation area and useful precipitation, as well as unpredictable information such as irrigation water allocation costs. Fei et al. [76] used multispectral data and ensemble learning to build ML including Cubist, support vector machine deep neural network, ridge regression, and random forest (RF) for wheat grain yield prediction. They examined the yield prediction capabilities of low, moderate, and higher watering regimens. The results demonstrated that low-altitude unmanned aerial vehicle-based multispectral data may be used to estimate early grain yields with high precision utilizing data fusion and an ensemble learning framework. Cui [77] described the agricultural landscaping and optimization plan and noticed some improvement in water storage for rice, wheat, maize and potatoes. Manikandakumar and Karthikeyan [27] used CNN with a powerful Particle Swarm Optimization (PSO) algorithm to improve and increase weed classification accuracy. CNN model significantly improves the success rate by 97.79% -

98.58%. Table 4 shows the gist of factors used in predicting the wheat crop yield by researchers.

Table 4: The gist of factors studied in research articles

Article	Factors used for predicting wheat crop yield	Performance Metrics	Data	Study Area	Techniques
[5]	Temperature, specific humidity, evaporation	RMSE	Climate data	India	RNN-LSTM
[27]	Image is normal or weed image	Accuracy	Weed images	India	CNN and PSO
[30]	NDVI, EVI	Precision, recall, F1 score, Accuracy	Sentinel-2	China	U-Net
[32]	LAI	R^2, RMSE	MODIS LAI	China	LSTM
[34]	Leaf parameters at tillering, stem elongation, flowering and grain filling	R^2, RMSE, MAE	Remote images	Iran	DNN
[36]	LAI	RMSE, MSE	Images	China	LSTM
[37]	Climate characteristics, NDVI	R^2, RMSE, MAE	Landsat-7	Australia	MLP
[38]	NDVI, LAI soil characteristics, weather condition	R^2, RMSE, MAPE, MAE	Satellite data	China	LSTM
[39]	NDVI, temperature, precipitation, day length	Accuracy	MODIS band and climate data	India	DNN
[40]	NDVI	Precision, Recall, F1-score, Kappa	Landsat 8	United State	DL
[41]	Features from images	RMSE	Images using UAV	USA	DNN MLP
[42]	Climate	MAE MAPE	UAV images	Finland	CNN
[43]	Climate and soil condition, NDVI, NDWI, EVI, GCI	R^2, RMSE, MAE	Satellite images, soil and climate data	United States	DNN
[45]	VI	RMSE	Sentinel-1and 2	Ethiopia	DNN
[46]	LAI	-	Remote sensed data	Guanzhong	GRU
[47]	LAI, vegetation temp condition index meteorological traits	R^2, RMSE	Remotely sense and meteorological data	China	GAN
[48]	LAI, meteorological, vegetation temperature condition index	R^2, RMSE, MAPE	Images and meteorological data	China	LSTM
[49]	Climate, LAI, VI	R^2, RMSE, MAPE	Remote images	China	LSTM
[50]	LAI	R^2, RMSE	Sentinel-2 data	China	LSTM
[52]	Spikelet from colour images	R^2, RMSE	Colour images	China	CNN
[53]	Spike count	RMSE	RGB image series	-	CNN
[54]	Spikelet	Precision, Recall, F1-Score	Images of single plant	India	CNN
[55]	Spike	RMSE	Wheat images	UK	U-Net, VGG-16
[56]	Features from crop image dataset	Precision, Recall, F1 Score, RMSE, MAPE	Annotated Crop Image Dataset	-	UNet
[58]	Spikelet	Precision, Recall, Accuracy	Images	Australia	R-CNN
[59]	Features from hyperspectral data	R^2, RMSE	Hyperspectral data acquisition	China	DNN
[60]	Relative water content, soil moisture content, Temperature	Accuracy, Sensitivity, Specificity, Precision, F1 Score	Collected thermal and RGB images labelled into stressed and non-stressed	India	DL-LSTM
[62]	Climate, soil properties	R^2, RMSE	Google Earth Engine platform	China	LSTM
[65]	Temperature, air pressure, specific humidity, wind speed, radiation, precipitation rate. Clay, silt, sand content, coarse fragments, and bulk density of soil	R^2, RMSE	Remote sensed data, weather, and soil data	China	VGG, ResNet, LSTM, DenseNet, GRU
[66]	Salinity, moisture, organic carbon of soil	R^2, MAE, RMSE	Sentinel	USA	MLP
[67]	Soil health, crop production, rainfall	MAE, RMSE, MSE, R^2, MAPE	Soil health, crop production and rainfall data	India	DNN
[68]	Soil characteristics	MSE	Soil test report	India	CNN
[69]	Soil traits	RMSE	Images and soil data	Australia	CNN
[70]	Weather, Soil condition, Ph, water content, carbon content	R^2, RMSE, MAPE	MODIS data,	United State	RNN and CNN
[71]	Features from images of aphids	-	1100 Wheat images of aphids	China	CNN
[72]	Features yellow rust infected and healthy leaves images	Accuracy	Images	India	CNN
[73]	Wheat diseases	Accuracy	Wheat diseases images	China	CNN
[75]	Rainfall, precipitation, irrigation water costs	Accuracy	Weather and Soil data	China	LSTM
[76]	Crop height, texture and VI	R^2, RMSE	Images taken by a drone	China	DNN
[77]	Air pressure, temperature humidity, soil temperature humidity	Compare	Images and weather, soil data	China	DRL
[78]	Features from images of crop	Recall, MAPE	Images of spider mite	China	ResNet
[79]	Weather, soil, and crop phenology	RMSE, MAE	Dataset of weather, soil, and crop phenology	Germany	DNN, CNN, and XGBoost
[80]	Features from Sentinel-2 data	F1 score	Sentinel-2	China	Conv1D, LSTM, RF, SVM
[81]	Genomic phenotypic	Pearson's correlation co-efficient	Genomic and phenotypic data	Europe	Bayesian
[82]	Features from images of crop	Accuracy, Kappa, Dice	Images	China	ResNet Encoder-Decoder
[83]	Features from images of wheat crop	MAE, RMSE	3,373 RGB images	Europe, North America, Asia, and Australia	Encoder-Decoder CNN
[84]	Wheatears	F1-score	Photos of a wheat field	-	CNN
[85]	Phenological traits	F1 score	Geotagged pictures	Netherlands	CNN
[86]	Image is normal or weed image	Precision	Images	-	VGG16
[87]	Features from images of leaves, panicles and stems	F1-score	Images	Germany Spain	CNN
[88]	Features from images of wheat crop	Accuracy, Precision, Recall, F1-score	Images through drone	UK	ResNet
[89]	Phenological characteristics	F1 score	Sentinel-2	China	U-Net
[90]	Harvested yield quintals per hectare	R^2, RMSE	Yield data	Algeria	DNN
[91]	Healthy resistant and susceptible class for yellow rust disease	Accuracy, Precision, Recall, F1-score	Wheat rust disease images	Pakistan	ML
[92]	Wheat yield, planting area, satellite images and climate traits	R^2, RMSE	Wheat yield, planting area, satellite and climate data from various sources	India	LSTM
[93]	Features from images for healthy, resistant, and susceptible classes	Accuracy	1922 images	Pakistan.	GAN
[94]	Physiological traits measured on the leaf	MSE	Wheat leaves	Australia	CNN
[95]	Spatial and temporal features	R^2, RMSE, MAPE	MODIS sensor	China	RNN
[96]	Features from disease images	Accuracy	Leaf, stem, yellow rust, powdery mildew, and septoria disease images	Russia	CNN
[97]	Vegetation Index	Accuracy	Satellite Images	Israel	LSTM
[98]	Wheat ears/ spikelets	Counting accuracy rate	Images of wheat crop	-	CNN
[99]	Detection of mites on images of crop	Accuracy	Images of crop	China	VGG16

[100]	Detection of rust in images	Accuracy, Precision, Recall	Camera images of wheat	Germany	Deep ResNet
[101]	Features from disease images	Accuracy	138,000 images	Ireland	VGG19
[35]	NDVI, vegetation index	R^2, RMSE, MAE	Satellite imagery	Kazakhstan	SVM
[102]	Wheat rust disease	Accuracy, Precision, Recall	Optical photos of wheat at various phases of development	Pakistan	ResNet18
[103]	Leaf and spike disease	Precision, Recall, F1-score	Wheat spikes and leaf images.	India	VGG16 ResNet50
[104]	Vegetation Index	Precision, Recall, F1-Score	Images through aerial flights	United States	DNN
[105]	NDVI	Precision, Recall, F1-Score	Planet-Scope imageries Sentinel-2	Pakistan	CNN
[106]	Wheat ears	RMSE, Precision, Recall, F1-Score	Images of wheat ears were taken at the time of blossoming and filling	China	CNN
[107]	Spikelet	Precision, Recall, F1-Score	Images of wheat plants	-	R-CNN
[108]	Spikelet density, grain weight per spike, number of seeds per spike, peduncle and stem length	R^2	Samples in greenhouse	Iran	SVM, Clustering
[109]	Disease detection	R^2, RMSE	Colour images	USA	K-means, RCNN
[110]	MODIS, weather parameters	RMSE	MODIS data	USA	CNN-LSTM
[111]	NDVI	Precision, Recall, F1-score accuracy	UAV images	China	ResNet
[112]	Disease classification	Accuracy	8178 images	Europe	ResNet
[113]	Features from images	RMSE	UAV images	Mexico	AlexNet, VGG
[114]	Spikelet	Accuracy	Images	UK	CNN

3.3 Performance Parameters

Statistical metrics coefficient of determination (R^2), mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), precision, recall and Kappa coefficient were used to assess the predictive models' robustness. The crop yield prediction depends on more than one independent variable. So, Equation (5) predicts crop yield (C_{yld}), written as:

$$C_{yld} = w_0 + w_1 v_1 + w_2 v_2 + w_3 v_3 + \cdots + w_n v_n + \beta \qquad (5)$$

where C_{yld} is the crop yield that is to be determined, w_0 is the fittest model's y-intercept, $v_1, v_2, v_3 \ldots v_n$ are the values of the variables that affect yield, $w_1, w_2, w_3 \ldots w_n$ are the model coefficients, which are defined as the amounts by which yield changes as a result of changes in the corresponding variables [32].

The crop yield is predicted (P_C_{yld}), once the model has been developed using DL techniques. The model is assessed by using statistical metrics, taking into account C_{yld} and P_C_{yld} for *n* observations.

3.3.1 Coefficient of determination (R^2)

R^2 determines the proportion of crop yield variance that can be accounted for by the various factors. Equation (6) represents the mathematical expression for coefficient of correlation (*r*).

$$r = \frac{n\sum_{i=1}^{n} C_{yld_i} * P_{C_{yld_i}} - \sum_{i=1}^{n} C_{yld_i} * \sum_{i=1}^{n} P_{C_{yld_i}}}{\left(\sqrt{n\sum_{i=1}^{n} C_{yld_i}{}^2 - \left(\sum_{i=1}^{n} C_{yld_i}\right)^2}\right) * \left(\sqrt{n\sum_{i=1}^{n} P_{C_{yld}}{}^2 - \left(\sum_{i=1}^{n} P_{C_{yld}}\right)^2}\right)} \qquad (6)$$

To understand statistical correlation using the '*r*', Sharma & Singh [115] provide the following general rules:

- If the value of *r* is between 0.68 to 1 then there is a strong correlation between C_{yld} and P_C_{yld}
- If the value of *r* is between 0.36 to 0.67 then there is a moderate correlation between C_{yld} and P_C_{yld}
- If the value of *r* is less than 0.35 then there is a weak correlation between C_{yld} and P_C_{yld}

R^2 which ranges from 0 to 1, is the square of the correlation coefficient (*r*) [115] expressed in Equation (7).

$$R^2 = (r)^2 \qquad (7)$$

The parameters being utilized to predict crop yield are not good if R^2 is close to zero, while the crop yield can be estimated error-free when its value is 1. R^2 is a relative measure of fit.

3.3.2 Root mean square error (RMSE)

RMSE is a unit of measurement for the standard deviation of variations between actual values and predicted values. It is expressed with the square root of the average of the square of all the inaccuracies. It indicates the total fit of existing values to the predicted values. A lesser RMSE indicates a more accurate fit and responsiveness of the prediction model [115]. Equation (8) represents the mathematical expression for *RMSE*.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(C_{yld_i} - P_{C_{yld_i}}\right)^2}{n}} \qquad (8)$$

3.3.3 Mean absolute percentage error (MAPE)

MAPE calculates the percentage amount of the error and displays how closely the estimated value corresponds to the actual value. The discrepancy between actual crop yield and predicted crop yield is divided by the actual value of crop yield. For each predicted time point, this ratio's absolute value is added and then divided by the *n* fitted points. Due to its interpretability and scale independence, it is one of the most popular statistical metrics for gauging model accuracy [115]. Equation (9) represents the mathematical expression for MAPE.

https://doi.org/10.4314/njt.v43i4.12

$$MAPE = \frac{1}{n} * \left(\sum_{i=1}^{n} \frac{C_{yld_i} - P_{C_{yld_i}}}{C_{yld_i}} \right) * 100 \quad (9)$$

3.3.4 Mean absolute error (MAE)

MAE is a metric of errors between actual crop yield and predicted crop yield [115]. Equation (10) represents the mathematical expression for MAE.

$$MAE = \frac{\sum_{i=1}^{n} P_{C_{yld_i}} - C_{yld}}{n} \quad (10)$$

3.3.5 Accuracy

In supervised classification, accuracy is the evaluation index that is most frequently used. It consists of the fraction between the total number of samples and the number of samples that were correctly predicted. The model is more trustworthy when its accuracy is better. Equation (11) can be used to calculate accuracy [25].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

where true positivity (TP) and true negativity (TN) designate that the prediction is correct, and both the predicted and the existing value match. False positivity (FP) and False negativity (FN) imply a prediction error, that is, the expected value and the truth value do not match.

3.3.6 Precision

Precision is measured by the ratio of true positives to real results shown in Equation (12). Hence, precision evaluates each and every pertinent piece of evidence for the DL model. Precision aims to provide information about the accurate portion of positive identifiers or the number of relevant results [25].

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

3.3.7 Recall

Recall is the proportion of actual positive findings to those predicted results shown in Equation (13). Recall assists us in determining the accuracy of our prediction by analysing the given data. Recall provides an explanation for problems like what percentage of positive identifiers were successfully identified or how many of our findings were accurately classified, on average [25].

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

3.3.8 F1-score

F1-measure is the harmonic mean of precision and recall presented by Equation (14). In order to guarantee the correctness and inclusion of both precision and recall outcomes, the F1 measure is a more practical and appropriate way of classification [25].

$$F1 - score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (14)$$

3.3.9 Kappa coefficient

The Kappa coefficient is a measurement that contrasts actual accuracy with predicted accuracy [116]. The Kappa coefficient, which is used in the consistency test, often falls between 0 and 1. According to Landis and Koch, a score of 0-0.20 is considered low, 0.21-0.40 is OK, 0.41-0.60 is average, 0.61-0.80 is significant, and 0.81-1 is nearly ideal. Fleiss classifies Kappas of 0.40 as poor, 0.40-0.75 as acceptable to good, and 0.75 and above as excellent, noting that both scales are a little arbitrary is crucial [116]. The Kappa coefficient [116] can be calculated using Equation (15),

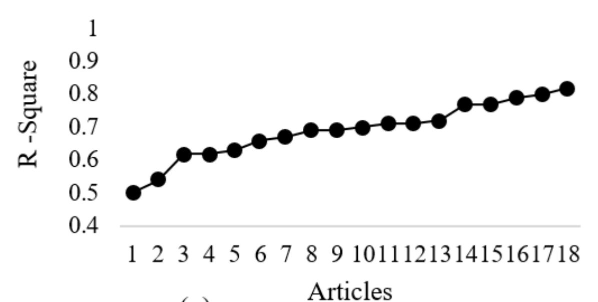
$$Kappa\ coefficient = \frac{\text{observed accuracy} - \text{expected accuracy}}{1 - \text{expected accuracy}} \quad (15)$$

3.3.10 Dice coefficient

For a function, the dice coefficient evaluates the degree of similarity among various sets and is normally employed to determine the closeness between two samples [82], ranging from 0 to 1. The dice coefficient is determined using Equation (16) [82].

$$Dice = \frac{2*TP}{FP+2*TP+FN} \quad (16)$$

Figure 12(a) – (d) show number of articles on X-axis with performance measures R-Square, RMSE, MAE and Accuracy on Y-axis respectively. It is observed that that the majority of researchers evaluated the DL model using the metrics of R^2 and accuracy. It is perceived that only 36% of the articles, had R^2 values larger than 0.8, accordingly there is an opportunity to improve R^2.



(a)

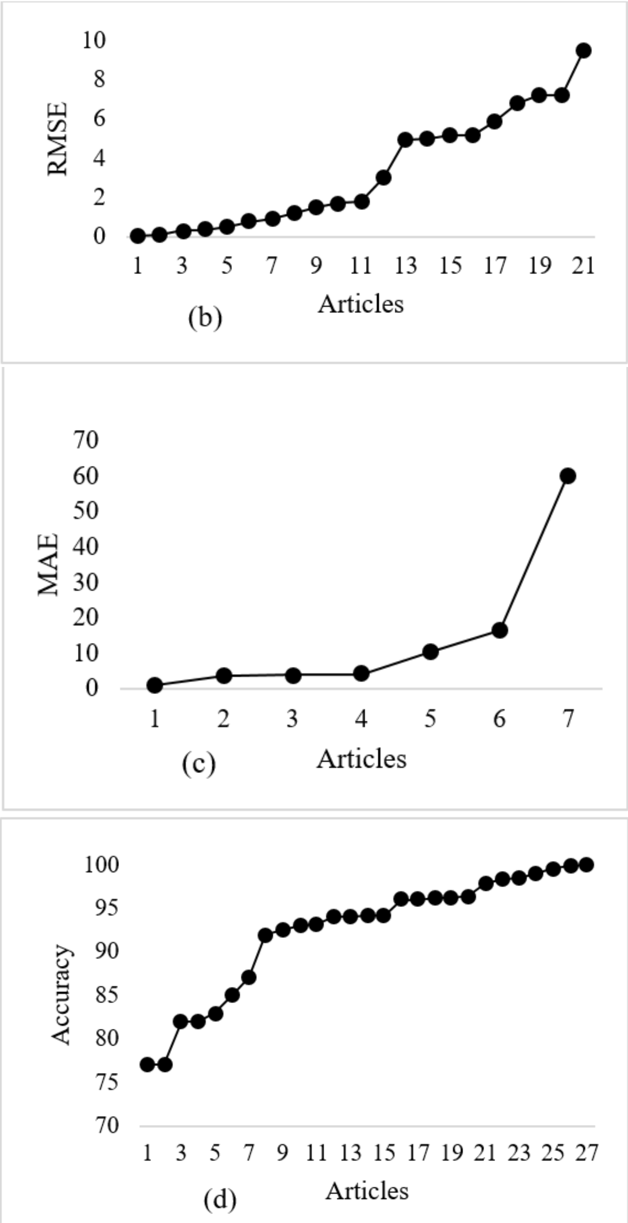


Figure 12: DL model performance metrics score from selected articles

3.3.11 Comparison of deep learning over machine learning

A substantial number of researchers used R^2 metrics to evaluate the DL model. After examining research papers considered in this article, it is noticed that LSTM-based technique is applied and proven to be the most successful. The researchers have evaluated and compared DL/ML strategies to figure out which approach delivers the greatest efficiency in terms of R^2 in predicting wheat yields. Table 5 summarizes some research publications that demonstrated a comparison of DL and ML techniques. As can be seen from Table 5, DL techniques perform better than ML techniques in terms of crop yield prediction since their R^2 value is larger.

Table 5: Performance of DL over ML

Article	Name of Technique	R^2	Type of Technique
[32]	LSTM	0.88	DL
	Support Vector Regression	0.76	ML
	Extreme Gradient Boosting	0.72	
	Random Forest	0.72	
[36]	LSTM	0.77	DL
	Random Forest	0.72	ML
[49]	BO-LSTM	0.82	DL
	Support Vector Machine	0.80	ML
	Least Absolute Shrinkage and Selection Operator Regression	0.76	
[50]	LSTM	0.92	DL
	Random Forest	0.72	ML
[60]	LSTM	0.96	DL
	Artificial Neural Network	0.93	
	Support Vector Machine	0.91	ML
	K-Nearest Neighbour	0.88	
	Logistic Regression	0.89	
[62]	DNN	0.85	DL
	LSTM	0.87	
	Random Forest	0.88	ML
[76]	DNN	0.60	DL
	Ridge Regression	0.55	ML
	Support Vector Machine	0.59	
	Random Forest	0.60	

4.0 CONCLUSIONS

An organized survey of recent research using DL techniques for estimating wheat crop yield is made available in this work. This comprehensive assessment presents different DL techniques, characteristics, and considerations used to estimate wheat crop yield. The research was conducted on various parameters and varied geography and places. In general, when measured against conventional ML algorithms, the success rate and efficiency of the DL methodology for crop yield prediction are better. Based on the parameters used in the model, all DL algorithms are equally effective. The LSTM-based technique, even so, is the most successful DL strategy for predicting agricultural productivity. As per the results of this study, it is concluded that the most utilized parameters are vegetation indexes and weather observations, where the vegetation indices describe the physical characteristics of the crops and the weather forecasts assist in monitoring the environmental conditions, which directly affect wheat crop yield prediction. Wheat crop diseases also impacted yield predictions. This study will contribute to a more thorough comprehension of how crop yield predictions are currently being made for wheat. The notion of predicting wheat crop production still has room for progress in the future, even though a considerable number of research articles are considered in this review.

REFERENCES

[1] Bari, P. and Ragha, L. "Machine learning-based extrapolation of crop cultivation cost", *Inteligencia Artificial*, vol. 27, no. 74, pp. 80–101, 2024, doi: 10.4114/intartif.vol27iss74pp 80-101.

[2] Islam, M. M., Adil, M. A. A., Talukder, M. A., Ahamed, M. K. U., Uddin, M. A., Hasan,

M. K., Sharmin, S., Rahman, M. M. and Debnath "DeepCrop: Deep learning-based crop disease prediction with web application", *Journal of Agriculture and Food Research*, vol. 14, no. August, p. 100764, 2023, doi: 10.1016/j.jafr.2023.100764.

[3] Statista "Wheat - statistics and facts", *Statista*, 2023. https://www.statista.com/topics/1668/wheat/#topicOverview (accessed Nov. 12, 2023).

[4] Agriculture "Wheat", *Vikaspedia*, 2020. https://vikaspedia.in/agriculture/crop-production/package-of-practices/cereals-and-millets/wheat (accessed Nov. 12, 2023).

[5] Bali, N. and Singla, A. "Deep learning based wheat crop yield prediction model in Punjab region of north India", *Applied Artificial Intelligence*, vol. 35, no. 15, pp. 1304–1328, 2021, doi: 10.1080/08839514.2021.1976091.

[6] Pant, J., Pant, R. P., Kumar Singh, M., Pratap Singh, D. and Pant, H. "Analysis of agricultural crop yield prediction using statistical techniques of machine learning", *Materials Today: Proceedings*, vol. 46, pp. 10922–10926, 2021, doi: 10.1016/j.matpr.2021.01.948.

[7] Ezeaku, C., Ani, A. O., Adama, J., Job, V., Sule, S., Onwualu, A., Nwankwojike, B., Otoijamun, I. and Ogbobe, P. "Willingness to adopt precision agriculture: An analysis of Gombe and Bauchi States of Nigeria", *Nigerian Journal of Technology*, vol. 43, no. 1, pp. 198–206, 2024, doi: 10.4314/njt.v43i1.21.

[8] Mcculloch, W. S. and Pitts, W. "A logical calculus of the ideas immanent in nervous activity", *Bulletin of Mothemntical Biophysics*, vol. 5, pp. 115–133, 1943.

[9] Rosenblatt, F. "The perceptron: A probabilistic model for information storage and organization in the brain", *Psychological Review*, vol. 65, no. 6, pp. 386–408, 1958, doi: 10.1037/h0042519.

[10] Kelley, H. J. "Gradient theory of optimal flight paths", *ARS Journal*, vol. 30, no. 10, pp. 947–954, 1960, doi: 10.2514/8.5282.

[11] Dreyfus, S. "The numerical solution of variational problems", *Journal of Mathematical Analysis and Applications*, vol. 5, no. 1, pp. 30–45, 1962, doi: 10.1016/0022-247X(62)90004-5.

[12] Fukushima, K. "Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position", *Biological Cybernetics*, vol. 36, no. 4, pp. 193–202, 1980, doi: 10.1007/BF00344251.

[13] Rumelhart, D. E., Hintont, G. E. and Williams, R. J. "Learning representations by back-propagating errors", *Nature*, vol. 323, pp. 533–536, 1986, doi: https://doi.org/10.1038/323533a0.

[14] LeCun, Y., Boser, B., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W. and Jackel, L. D. "Backpropagation applied to handwritten zip code recognition neural computation", *Neural Computation*, vol. 1, no. 4, pp. 541–551, 1989, doi: doi: 10.1162/neco.1989.1.4.541.

[15] Xu, X., Gao, P., Zhu, X., Guo, W., Ding, J., Li, C., Zhu, M. and Wu, X. "Design of an integrated climatic assessment indicator (ICAI) for wheat production: A case study in Jiangsu Province, China", *Ecological Indicators*, vol. 101, pp. 943–953, 2019, doi: 10.1016/j.ecolind.2019.01.059.

[16] Filippi, P., Jones, E. J., Wimalathunge, N. S., Somarathna, P. D. S. N., Pozza, L. E., Ugbaje, S. U., Jephcott, T. G., Paterson, S. E., Whelan, B. M. and Bishop, T. F. A. "An approach to forecast grain crop yield using multi-layered, multi-farm data sets and machine learning", *Precision Agriculture.*, vol. 20, no. 5, pp. 1015–1029, 2019, doi: 10.1007/s11119-018-09628-4.

[17] Klompenburg, T. van, Kassahun, A. and Catal, C. "Crop yield prediction using machine learning: A systematic literature review", *Computers and Electronics in Agriculture*, vol. 177, 2020, doi: 10.1016/j.compag.2020.105709.

[18] Muruganantham, P., Wibowo, S., Grandhi, S., Samrat, N. H. and Islam, N. "A systematic literature review on crop yield prediction with deep learning and remote sensing", *Remote Sensing*, vol. 14, no. 9, 2022, doi: 10.3390/rs14091990.

[19] Kitchenham, B., Charters, S., Budgen, D., Brereton, P., Turner, M., Linkman, S. and Visaggio, G. "Guidelines for performing systematic literature reviews in software engineering", *Technical Report, Ver. 2.3 EBSE Technical Report. EBSE*. 2007, doi: Retrieved from https://userpages.uni-koblenz.de/~laemmel/esecourse/slides/slr.pdf

[20] Bari, P. and Karande, P. "Cost factor focused scheduling and sequencing : A neoteric literature review", *Operational Research in Engineering Sciences: Theory and Applications*, vol. 6, no. 2, 2023, pp. 336-366

2022, doi: https:// doi.org/10.31181/oresta281 2222016b.

[21] Angermueller, C., Pärnamaa, T., Parts, L. and Stegle, O. "Deep learning for computational biology", *Molecular Systems Biology*, vol. 12, no. 7, 2016, doi: 10.15252/msb.20156651.

[22] Sandhu, K. S., Lozada, D. N., Zhang, Z., Pumphrey, M. O. and Carter, A. H. "Deep learning for predicting complex traits in spring wheat breeding program", *Frontiers in Plant Science*, vol. 11, 2021, doi: 10.3389/fpls.2020.613325.

[23] LeCun, Y., Leon, B., Yoshua, B. and Patrick, H. "Gradient-based learning applied to document recognition", *Proceedings IEEE*, vol. 86, no. 11, pp. 1299–1305, 1998, doi: 10.1109/5.726791.

[24] Karen, S. and Zisserman, A. "Very deep convolutional networks for large-scale image recognition", *International Conference on Learning Representations*, vol. 75, no. 6, pp. 398–406, 2015.

[25] Bari P. and Ragha L., "Optimizing pesticide decisions with deep transfer learning by recognizing crop pest", *First IEEE International Conference On "New Frontiers in Communication, Automation, Management and Security (ICCAMS-2023)", Presidency University, Bangalore*, 2023.

[26] Szegedy, C., Wei, L., Yangqing, J., Pierre, S., Scott, R., Dragomir, A., Dumitru, E., Vincent, V. and Andrew, R. "Going deeper with convolutions Christian", *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–9, 2015, doi: 10.1109/CVPR.2015.72 98594.

[27] Manikandakumar, M. and Karthikeyan, P. "Weed classification using particle swarm optimization and deep learning models", *Computer Systems Science and Engineering.*, vol. 44, no. 1, pp. 913–927, 2022, doi: 10.32604/csse.2023.025434.

[28] He, K., Zhang, X., Ren, S. and Sun, J. "Deep residual learning for image recognition", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 770–778, 2016, doi: 10.1109/CVPR.2016 .90.

[29] Ronneberger, O., Fischer, P. and Brox, T. "U-Net: Convolutional Networks for Biomedical Image Segmentation", *IEEE Access*, vol. 9, pp. 16591–16603, 2021, doi: 10.1109/ACCE SS.2021.3053408.

[30] Liu, S., Peng, D., Zhang, B., Chen, Z., Yu, L., Chen, J., Pan, Y., Zheng, S., Hu, J., Lou, Z., Chen, Y. and Yang, S. "The accuracy of winter wheat identification at different growth stages using remote sensing", *Remote Sensing*, vol. 14, no. 4, 2022, doi: 10.3390/rs 14040893.

[31] Graves, A. "Generating sequences with recurrent neural networks", *ArXiv Prepr*, pp. 1–43, 2013, http://arxiv.org/abs/1308.0850.

[32] Wang, J., Si, H., Gao, Z. and Shi, L. "Winter wheat yield prediction using an LSTM model from MODIS LAI products", *Agriculture*, vol. 12, no. 10, 2022, doi: 10.3390/agricultu re12101707.

[33] Huete, A. R., Liu, H. Q., Batchily, K. and Leeuwen, W. Van. "A comparison of vegetation indices over a global set of TM images for EOS-MODIS", *Remote Sensing of Environment.*, vol. 59, no. 1, pp. 440-451., 1997.

[34] Jamali, M., Soufizadeh, S., Yeganeh, B. and Emam, Y. "Wheat leaf traits monitoring based on machine learning algorithms and high-resolution satellite imagery", *Ecological Informatics*, vol. 74, 2023, doi: 10.1016/j.ecoinf.2022.101967.

[35] Beisekenov, N. A., Sadenova, M. A. and Varbanov, P. S. "Mathematical optimization as a tool for the development of 'Smart' agriculture in Kazakhstan", *Chemical Engineering Transactions*, vol. 88, pp. 1219–1224, 2021, doi: 10.3303/CET2188203.

[36] Xie, Y. and Huang, J. "Integration of a crop growth model and deep learning methods to improve satellite-based yield estimation of winter wheat in henan province, China", *Remote Sensing*, vol. 13, no. 21, 2021, doi: 10.3390/rs13214372.

[37] Evans, F. H. and Shen, J. "Long-term hindcasts of wheat yield in fields using remotely sensed phenology, climate data and machine learning", *Remote Sensing*, vol. 13, no. 13, 2021, doi: 10.3390/rs13132435.

[38] Wang, X., Huang, J., Feng, Q. and Yin, D. "Winter wheat yield prediction at county level and uncertainty analysis in main wheat-producing regions of China with deep learning approaches", *Remote Sensing*, vol. 12, no. 11, 2020, doi: 10.3390/rs12111744.

[39] Wolanin, A., Mateo-Garciá, G., Camps-Valls, G., Gómez-Chova, L., Meroni, M., Duveiller, G., Liangzhi, Y. and Guanter, L. "Estimating and understanding crop yields with explainable deep learning in the Indian wheat belt", *Environmental Research Letters*, vol. 15, no. 2, 2020, doi: 10.1088/1748-9326/ab68ac.

[40] Sun, Z., Di, L., Fang, H. and Burgess, A. "Deep learning classification for crop types in North Dakota", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, pp. 2200–2213, 2020, doi: 10.1109/JSTARS.2020.2990104.

[41] Moghimi, A., Yang, C. and Anderson, J. A. "Aerial hyperspectral imagery and deep neural networks for high-throughput yield phenotyping in wheat", *Computers and Electronics in Agriculture*, vol. 172, 2020, doi: 10.1016/j.compag.2020.105299.

[42] Nevavuori, P., Narra, N. and Lipping, T. "Crop yield prediction with deep convolutional neural networks", *Computers and Electronics in Agriculture*, vol. 163, 2019, doi: 10.1016/j.compag.2019.104859.

[43] Wang, Y., Zhang, Z., Feng, L., Du, Q. and Runge, T. "Combining multi-source data and machine learning approaches to predict winter wheat yield in the conterminous United States", *Remote Sensing*, vol. 12, no. 8, 2020, doi: 10.3390/RS12081232.

[44] Tanabe, R., Matsui, T. and Tanaka, T. S. T. "Winter wheat yield prediction using convolutional neural networks and UAV-based multispectral imagery", *Field Crops Research*, vol. 291, 2023, doi: 10.1016/j.fcr. 2022.108786.

[45] Tesfaye, A. A., Awoke, B. G., Sida, T. S. and Osgood, D. E. "Enhancing smallholder wheat yield prediction through sensor fusion and phenology with Machine Learning and Deep Learning methods", *Agriculture*, vol. 12, no. 9, 2022, doi: 10.3390/agriculture12091352.

[46] Han, D., Wang, P., Tansey, K., Liu, J., Zhang, Y., Tian, H. and Zhang, S. "Integrating an attention-based deep learning framework and the SAFY-V model for winter wheat yield estimation using time series SAR and optical data", *Computers and Electronics in Agriculture*, vol. 201, no. 17, p. 107334, 2022, doi: 10.1016/j.compag.2022.107334.

[47] Zhang, J., Tian, H., Wang, P., Tansey, K., Zhang, S. and Li, H. "Improving wheat yield estimates using data augmentation models and remotely sensed biophysical indices within deep neural networks in the Guanzhong Plain, PR China", *Computers and Electronics in Agriculture*, vol. 192, no. 17, 2022, doi: 10.1016/j.compag.2021.106616.

[48] Tian, H., Wang, P., Tansey, K., Han, D., Zhang, J., Zhang, S. and Li, H. "A deep learning framework under attention mechanism for wheat yield estimation using remotely sensed indices in the Guanzhong Plain, PR China", *International Journal of Applied Earth Observation and Geoinformation.*, vol. 102, no. 17, 2021, doi: 10.1016/j.jag.2021.102375.

[49] Di, Y., Gao, M., Feng, F., Li, Q. and Zhang, H. "A new framework for winter wheat yield prediction integrating deep learning and bayesian optimization", *Agronomy*, vol. 12, no. 12, pp. 1–15, 2022, doi: 10.3390/agronomy12123194.

[50] Xie, Y. "Combining CERES-Wheat model, Sentinel-2 data and deep learning method for winter wheat yield estimation", *International Journal of Remote Sensing*, vol. 43, no. 2, pp. 630–648, 2022, doi: 10.1080/01431161.2022.2026521.

[51] Wang, J., Wang, P., Tian, H., Tansey, K., Liu, J. and Quan, W. "A deep learning framework combining CNN and GRU for improving wheat yield estimates using time series remotely sensed multi-variables", *Computers and Electronics in Agriculture*, vol. 206, no. 17, 2023, doi: 10.1016/j.compag.2023.107705.

[52] Qiu, R., He, Y. and Zhang, M. "Automatic detection and counting of wheat spikelet using semi-automatic labeling and deep learning", *Frontiers in Plant Science*, vol. 13, pp. 1–11, 2022, doi: 10.3389/fpls.2022.872555.

[53] Alkhudaydi, T. and De La lglesia, B. "Counting spikelets from infield wheat crop images using fully convolutional networks", *Neural Computing and Applications*, vol. 34, no. 20, pp. 17539–17560, 2022, doi: 10.1007/s00521-022-07392-1.

[54] Misra, T., Arora, A., Marwaha, S., Chinnusamy, V., Rao, A. R., Jain, R., Sahoo, R. N., Ray, M., Kumar, S., Raju, D., Jha, R. R., Nigam, A. and Goel, S. "SpikeSegNet - A deep learning approach utilizing encoder-decoder network with hourglass for spike segmentation and counting in wheat plant from visual imaging", *Plant Methods*, vol. 16, no. 1, pp. 1–20, 2020, doi: 10.1186/s13007-020-00582-9.

[55] Sadeghi-Tehran, P., Virlet, N., Ampe, E. M., Reyns, P. and Hawkesford, M. J. "Deepcount: In-field automatic quantification of wheat spikes using simple linear iterative clustering and deep convolutional neural networks", *Frontiers in Plant Science*, vol. 10, pp. 1–16, 2019, doi: 10.3389/fpls.2019.01176.

[56] Zaji, A., Liu, Z., Xiao, G., Bhowmik, P.,

Sangha, J. S. and Ruan, Y. "Wheat spike localization and counting via hybrid UNet architectures", *Computers and Electronics in Agriculture*, vol. 203, 2022, doi: 10.1016/j.compag.2022.107439.

[57] Chen, J., Li, Q., Tan, Q., Gui, S., Wang, X., Yi, F., Jiang, D. and Zhou, J. "Combining lightweight wheat spikes detecting model and offline Android software development for in-field wheat yield prediction", *Nongye Gongcheng Xuebao/Transactions of the Chinese Society of Agricultural Engineering*, vol. 37, no. 19, pp. 156–164, 2021, doi: 10.11975/j.issn.1002-6819.2021.19.018.

[58] Hasan, M. M., Chopin, J. P., Laga, H. and Miklavcic, S. J. "Detection and analysis of wheat spikes using Convolutional Neural Networks", *Plant Methods*, vol. 14, no. 1, pp. 1–13, 2018, doi: 10.1186/s13007-018-0366-8.

[59] Fei, S., Li, L., Han, Z., Chen, Z. and Xiao, Y. "Combining novel feature selection strategy and hyperspectral vegetation indices to predict crop yield", *Plant Methods*, vol. 18, no. 1, pp. 1–13, https://doi.org/10.1186/s13007-022-00949-0.

[60] Chandel, N. S., Rajwade, Y. A., Dubey, K., Chandel, A. K., Subeesh, A. and Tiwari, M. K. "Water stress identification of winter wheat crop with, state-of-the-art AI techniques and high-resolution thermal-RGB imagery", *Plants*, pp. 2–21, 2022, doi: https://doi.org/10.3390/ plants11233344.

[61] Adesanya, O. O. and Yinka-Banjo, C. O. "Classification of nitrogen deficiency for maize plants using deep learning algorithms on low-end android smartphones", *Nigerian Journal of Technology*, vol. 41, no. 2, pp. 278–290, 2022, doi: 10.4314/njt.v41i2.10.

[62] Cao, J., Zhang, Z., Luo, Y., Zhang, L., Zhang, J., Li, Z. and Tao, F. "Wheat yield predictions at a county and field scale with deep learning, machine learningand google earth engine", *European Journal of Agronomy.*, vol. 123, 2021, doi: 10.1016/j.eja.2020.126204.

[63] Kaur, A., Goyal, P., Rajhans, R., Agarwal, L. and Goyal, N. "Fusion of multivariate time series meteorological and static soil data for multistage crop yield prediction using multi-head self attention network", *Expert Systems with Applications*, vol. 226, 2023, doi: 10.1016/j.eswa.2023.120098.

[64] Paudel, D., de Wit, A., Boogaard, H., Marcos, D., Osinga, S. and Athanasiadis, I. N. "Interpretability of deep learning models for crop yield forecasting", *Computers and Electronics in Agriculture*, vol. 206, 2023, doi: 10.1016/j.compag.2023.107663.

[65] Huang, H., Huang, J., Feng, Q., Liu, J., Li, X., Wang, X. and Niu, Q. "Developing a dual-stream deep-learning neural network model for improving county-level winter wheat yield estimates in China", *Remote Sensing*, vol. 14, no. 20, 2022, doi: 10.3390/rs14205280.

[66] Tripathi, A., Tiwari, R. K. and Tiwari, S. P. "A deep learning multi-layer perceptron and remote sensing approach for soil health based crop yield estimation", *International Journal of Applied Earth Observation and Geoinformation.*, vol. 113, 2022, doi: 10.1016/j.jag.2022.102959.

[67] Kumar, R. and Pandey, S. "An accurate prediction of crop yield using hybrid deep capsule auto encoder with softmax regression", *Multimedia Tools and Applications*, vol. 82, no. 10, pp. 15371–15393, 2023, doi: 10.1007/s11042-022-13919-4.

[68] Daniel, J., Shyamala, R., Pugalenthi, R. and Mohan Kumar, P. "RANC-CROP recommendation attributed to soil nutrients and stock analysis using machine learning", *IETE Journal of Research*, 2022, doi: 10.1080/03772063.2022.2060868.

[69] Fajardo, M. and Whelan, B. M. "Within-farm wheat yield forecasting incorporating off-farm information", *Precision Agriculture*, vol. 22, no. 2, pp. 569–585, 2021, doi: 10.1007/s11119-020-09779-3.

[70] Sun, J., Lai, Z., Di, L., Sun, Z., Tao, J. and Shen, Y. "Multilevel deep learning network for county-level corn yield estimation in the U.S. corn belt", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, pp. 5048–5060, 2020, doi: 10.1109/JSTARS.2020.3019046.

[71] Li, R., Wang, R., Xie, C., Chen, H., Long, Q., Liu, L., Zhang, J., Chen, T., Hu, H., Jiao, L., Du, J. and Liu, H. "A multi-branch convolutional neural network with density map for aphid counting", *Biosystems Engineering*, vol. 213, pp. 148–161, 2022, doi: 10.1016/j.biosystemseng.2021.11.020.

[72] Nigam, S., Jain, R., Marwaha, S., Arora, A., Singh, V. K., Singh, A. K., Paul, R. K. and Kingsly, I. T. "Automating yellow rust disease identification in wheat using artificial intelligence", *Indian Journal of Agricultural Sciences*, vol. 91, no. 9, pp. 1391–1395, 2021, doi: 10.56093/ijas.v91i9.116097.

[73] Jiang, J., Liu, H., Zhao, C., He, C., Ma, J., Cheng, T., Zhu, Y., Cao, W. and Yao, X. "Evaluation of diverse convolutional neural networks and training strategies for wheat leaf disease identification with field-acquired photographs", *Remote Sensing*, vol. 14, no. 14, 2022, doi: 10.3390/rs14143446.

[74] Long, M., Hartley, M., Morris, R. J. and Brown, J. K. M. "Classification of wheat diseases using deep learning networks with field and glasshouse images", *Plant Pathology*, vol. 72, no. 3, pp. 536–547, 2023, doi: 10.1111/ppa.13684.

[75] Jia, W., Wei, Z. and Zhang, L. "A novel prediction and planning model for the benefit of irrigation water allocation based on deep learning and uncertain programming", *Water*, vol. 14, no. 5, 2022, doi: //doi.org/10.3390/w14050689.

[76] Fei, S., Hassan, M. A., Xiao, Y., Su, X., Chen, Z., Cheng, Q., Duan, F., Chen, R. and Ma, Y. "UAV-based multi-sensor data fusion and machine learning algorithm for yield prediction in wheat", *Precision Agriculture*, vol. 24, no. 1, pp. 187–212, 2023, doi: 10.1007/s11119-022-09938-8.

[77] Cui, Y. "Landscaping agricultural and animal husbandry production park using lightweight deep reinforcement learning under circular symbiosis concept", *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–8, 2022, doi: 10.1155/2022/8410996.

[78] Pang, D., Wang, H., Chen, P. and Liang, D. "Spider mites detection in wheat field based on an improved RetinaNet", *Agriculture (Switzerland)*, vol. 12, no. 12, pp. 1–14, 2022, doi: 10.3390/agriculture12122160.

[79] Srivastava, A. K., Safaei, N., Khaki, S., Lopez, G., Zeng, W., Ewert, F., Gaiser, T. and Rahimi, J. "Winter wheat yield prediction using convolutional neural networks from environmental and phenological data", *Scientific Reports*, vol. 12, no. 1, pp. 1–14, 2022, doi: 10.1038/s41598-022-06249-w.

[80] Yi, Z., Jia, L., Chen, Q., Jiang, M., Zhou, D. and Zeng, Y. "Early-season crop identification in the Shiyang river basin Using a deep learning algorithm and time-series Sentinel-2 data", *Remote Sensing*, vol. 14, no. 21, 2022, doi: 10.3390/rs14215625.

[81] Sirsat, M. S., Oblessuc, P. R. and Ramiro, R. S. "Genomic prediction of wheat grain yield using machine learning", *Agriculture*, vol. 12, no. 9, 2022, doi: 10.3390/agriculture12091406.

[82] Jiang, S., Hao, J., Li, H., Zuo, C., Geng, X. and Sun, X. "Gradient theory of optimal flight paths", *Sensors*, vol. 22, no. 18, pp. 1–20, 2022, doi: 10.3390/s22186967.

[83] Khaki, S., Safaei, N., Pham, H. and Wang, L. "WheatNet: A lightweight convolutional neural network for high-throughput image-based wheat head detection and counting", *Neurocomputing*, vol. 489, pp. 78–89, 2022, doi: 10.1016/j.neucom.2022.03.017.

[84] Tereshchenko, S. N., Osipov, A. L. and Moiseeva, E. D. "Determining the number of wheatears on the images of wheat fields by the computer vision method", *Optoelectronics, Instrumentation and Data Processing*, vol. 58, no. 3, pp. 266–272, 2022, doi: 10.3103/S8756699022030074.

[85] d'Andrimont, R., Yordanov, M., Martinez-Sanchez, L. and van der Velde, M. "Monitoring crop phenology with street-level imagery using computer vision", *Computers and Electronics in Agriculture*, vol. 196, 2022, doi: 10.1016/j.compag.2022.106866.

[86] Indira, D. N., Sobhana, M., Sumallika, T. and Sudha, M. V. "An artificial intelligence based weed classification using vgg16 classifier and rmsprop optimizer", *Journal of Theoretical and Applied Information Technology*, vol. 100, no. 7, pp. 1806–1816, 2022.

[87] Egusquiza, I., Picon, A., Irusta, U., Bereciartua-Perez, A., Eggers, T., Klukas, C., Aramendi, E. and Navarra-Mestre, R. "Analysis of few-shot techniques for fungal plant disease classification and evaluation of clustering capabilities over real datasets", *Frontiers in Plant Science*, vol. 13, pp. 1–17, 2022, doi: 10.3389/fpls.2022.813237.

[88] Zhang, X., Han, L., Sobeih, T., Lappin, L., Lee, M. A., Howard, A. and Kisdi, A. "The self-supervised spectral–spatial vision transformer network for accurate prediction of wheat nitrogen status from UAV imagery", *Remote Sensing*, vol. 14, no. 6, 2022, doi: 10.3390/rs14061400.

[89] Qi, X., Wang, Y., Peng, J., Zhang, L., Yuan, W. and Qi, X. "The 10-meter winter wheat mapping in Shandong province using sentinel-2 data and coarse resolution maps", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 9760–9774, 2022, doi: 10.1109/JSTARS.2022.3220698.

[90] Chergui, N. "Durum wheat yield forecasting using machine learning", *Artificial Intelligence in Agriculture*, vol. 6, pp. 156–166, 2022,

doi: 10.1016/j.aiia.2022.09.003.
[91] Shafi, U., Mumtaz, R., Haq, I. U., Hafeez, M., Iqbal, N., Shaukat, A., Zaidi, S. M. H. and Mahmood, Z. "Wheat yellow rust disease infection type classification using texture features", *Sensors*, vol. 22, no. 1, pp. 1–21, 2022, doi: 10.3390/s22010146.
[92] Liu, Y., Wang, S., Wang, X., Chen, B., Chen, J., Wang, J., Huang, M., Wang, Z., Ma, L., Wang, P., Amir, M. and Zhu, K. "Exploring the superiority of solar-induced chlorophyll fluorescence data in predicting wheat yield using machine learning and deep learning methods", *Computers and Electronics in Agriculture*, vol. 192, pp. 1–11, 2022, doi: 10.1016/j.compag.2021.106612.
[93] Maqsood, M. H., Mumtaz, R., Haq, I. U., Shafi, U., Zaidi, S. M. H. and Hafeez, M. "Super resolution generative adversarial network (Srgans) for wheat stripe rust classification", *Sensors*, vol. 21, no. 23, pp. 1–12, 2021, doi: 10.3390/s21237903.
[94] Furbank, R. T., Silva-Perez, V., Evans, J. R., Condon, A. G., Estavillo, G. M., He, W., Newman, S., Poiré, R., Hall, A. and He, Z. "Wheat physiology predictor: Predicting physiological traits in wheat from hyperspectral reflectance measurements using deep learning", *Plant Methods*, vol. 17, no. 1, pp. 1–15, 2021, doi: 10.1186/s13007-021-00806-6.
[95] Qiao, M., He, X., Cheng, X., Li, P., Luo, H., Zhang, L. and Tian, Z. "Crop yield prediction from multi-spectral, multi-temporal remotely sensed imagery using recurrent 3D convolutional neural networks", *International Journal of Applied Earth Observation and Geoinformation.*, vol. 102, 2021, doi: 10.1016/j.jag.2021.102436.
[96] Genaev, M. A., Skolotneva, E. S., Gultyaeva, E. I., Orlova, E. A., Bechtold, N. P. and Afonnikov, D. A. "Image-based wheat fungi diseases identification by deep learning", *Plants*, vol. 10, no. 8, 2021, doi: 10.3390/plants10081500.
[97] Arun, P. V. and Karnieli, A. "Deep learning-based phenological event modeling for classification of crops", *Remote Sensing*, vol. 13, no. 13, pp. 1–23, 2021, doi: 10.3390/rs13132477.
[98] Wang, Y., Qin, Y. and Cui, J. "Occlusion robust wheat ear counting algorithm based on deep learning", *Frontiers in Plant Science*, vol. 12, no. June, pp. 1–14, 2021, doi: 10.3389/fpls.2021.645899.
[99] Chen, P., Li, W. L., Yao, S. J., Ma, C., Zhang, J., Wang, B., Zheng, C. H., Xie, C. J. and Liang, D. "Recognition and counting of wheat mites in wheat fields by a three-step deep learning method", *Neurocomputing*, vol. 437, pp. 21–30, 2021, doi: 10.1016/j.neucom.2020.07.140.
[100] Schirrmann, M., Landwehr, N., Giebel, A., Garz, A. and Dammer, K. H. "Early detection of stripe rust in winter wheat using deep residual neural networks", *Frontiers in Plant Science*, vol. 12, no. March, pp. 1–14, 2021, doi: 10.3389/fpls.2021.469689.
[101] Rasti, S., Bleakley, C. J., Silvestre, G. C. M., Holden, N. M., Langton, D. and O'Hare, G. M. P. "Crop growth stage estimation prior to canopy closure using deep learning algorithms", *Neural Computing and Applications*, vol. 33, no. 5, pp. 1733–1743, 2021, doi: 10.1007/s00521-020-05064-6.
[102] Bukhari, H. R., Mumtaz, R., Inayat, S., Shafi, U., Haq, I. U., Zaidi, S. M. H. and Hafeez, M. "Assessing the impact of segmentation on wheat stripe rust disease classification using computer vision and deep learning", *IEEE Access*, vol. 9, pp. 164986–165004, 2021, doi: 10.1109/ACCESS.2021.3134196.
[103] Goyal, L., Sharma, C. M., Singh, A. and Singh, P. K. "Leaf and spike wheat disease detection and classification using an improved deep convolutional architecture", *Informatics in Medicine Unlocked*, vol. 25, 2021, doi: 10.1016/j.imu.2021.100642.
[104] Sapkota, B., Singh, V., Neely, C., Rajan, N. and Bagavathiannan, M. "Detection of Italian ryegrass in wheat and prediction of competitive interactions using remote-sensing and machine-learning techniques", *Remote Sensing*, vol. 12, no. 18, 2020, doi: 10.3390/RS12182977.
[105] Minallah, N., Tariq, M., Aziz, N., Khan, W., ur Rehman, A. and Belhaouari, S. B. "On the performance of fusion based planet-scope and Sentinel-2 data for crop classification using inception inspired deep convolutional neural network", *PLoS One*, vol. 15, no. 9, pp. 1–16, 2020, doi: 10.1371/journal.pone.0239746.
[106] Xu, Xin, Li, H., Yin, F., Xi, L., Qiao, H., Ma, Z., Shen, S., Jiang, B. and Ma, X. "Wheat ear counting using K-means clustering segmentation and convolutional neural network", *Plant Methods*, vol. 16, no. 106, pp. 1–13, 2020, doi: 10.1186/s13007-020-00648-8.
[107] Chandra, A. L., Desai, S. V., Balasubraman

ian, V. N., Ninomiya, S. and Guo, W. "Active learning with point supervision for cost-effective panicle detection in cereal crops", *Plant Methods*, vol. 16, no. 34, pp. 1–16, 2020, doi: 10.1186/s13007-020-00575-8.

[108] Azimi, N., Sofalian, O., Davari, M., Asghari, A. and Zare, N. "Statistical and machine learning-based FHB detection in durum wheat", *Plant Breeding and Biotechnology*, vol. 8, no. 3, pp. 265–280, 2020, doi: 10.9787/PBB.2020.8.3.265.

[109] Qiu, R., Yang, C., Moghimi, A., Zhang, M., Steffenson, B. J. and Hirsch, C. D. "Detection of Fusarium Head Blight in wheat using a deep neural network and color imaging", *Remote Sensing*, vol. 11, no. 22, 2019, doi: 10.3390/rs11222658.

[110] Sun, J., Di, L., Sun, Z., Shen, Y. and Lai, Z. "County-level soybean yield prediction using deep CNN-LSTM model", *Sensors (Switzerland)*, vol. 19, no. 20, pp. 1–21, 2019, doi: 10.3390/s19204363.

[111] Zhang, X., Han, L., Dong, Y., Shi, Y., Huang, W., Han, L., González-Moreno, P., Ma, H., Ye, H. and Sobeih, T. "A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images", *Proceedings IEEE*, vol. 11, 2019, doi: 10.3390/rs11131554.

[112] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J. and Johannes, A. "Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild", *Computers and Electronics in Agriculture*, vol. 161, pp. 280–290, 2019, doi: 10.1016/j.compag.2018.04.002.

[113] Escalante, H. J., Rodríguez-Sánchez, S., Jiménez-Lizárraga, M., Morales-Reyes, A., De La Calleja, J. and Vazquez, R. "Barley yield and fertilization analysis from UAV imagery: A deep learning approach", *International Journal of Remote Sensing*, vol. 40, no. 7, pp. 2493–2516, 2019, doi: 10.1080/01431161.2019.1577571.

[114] Alkhudaydi, T., Reynolds, D., Griffiths, S., Zhou, J. and de la Iglesia, B. "An exploration of deep-learning based phenotypic analysis to detect spike regions in field conditions for UK bread wheat", *Plant Phenomics*, vol. 2019, pp. 1–17, 2019, doi: 10.34133/2019/7368761.

[115] Sharma, L. K. and Singh, T. N. "Regression-based models for the prediction of unconfined compressive strength of artificially structured soil", *Engineering with Computers*, vol. 34, no. 1, pp. 175–186, 2018, doi: 10.1007/s00366-017-0528-8.

[116] Yang W., Nigon T., Hao Z., Dias Paiao G.,. Fernández G., Mulla D., Yang C., "Estimation of corn yield based on hyperspectral imagery and convolutional neural network", *Computers and Electronics in Agriculture.*, vol. 184, 2021, doi: 10.1016/j.compag.2021.106092.