AVE **Trends in Intelligent Computing Systems**

Sustainable Crop Yield Prediction Using Machine Learning Algorithms

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Abstract: One of India's main economies, agriculture employs over half of the workforce. The industry faces many climatic risks, environmental degradation, and other externalities issues. Thus, researchers increasingly use machine learning (ML) methods to improve crop yield prediction. The research rigorously evaluates and incorporates dominant CYP features, reacting to varied techniques with artificial intelligence for agricultural productivity forecasts. It aims to develop reliable, efficient crop categorization and yield prediction methods to improve agricultural innovation. Comparing agricultural yield prediction ML methods is a key aspect of the work. These methods use climate, plant health, and growth stage datasets. Integrating such information, the scientists aim to develop models that accurately estimate yields, enabling agricultural producers to make informed decisions. This article compares ML agricultural yield prediction methods point-by-point. It details their performance, strengths, and weaknesses, and closes with the best way to improve agricultural production. The publication concludes by outlining future agricultural ML research areas. It emphasizes the need for ongoing innovation and integration of existing methods to meet agricultural industry objectives. The book aims to improve agricultural yield forecasts and promote sustainable agriculture by facilitating communication among farmers, policymakers, and researchers.

Keywords: Crop Yield Prediction (CYP); Machine Learning (ML) Algorithms; Agricultural Stakeholders; Weather Conditions; Climate Changes; Food Availability.

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1. Introduction

Early crop yield prediction is among the drivers of food security through key information on food availability to feed an expanding population, as outlined by Kamilaris and Prenafeta-Boldú [1]. As the population continues to grow, there is an urgent need to enhance agricultural productivity in a bid to meet these needs. Eradicating world hunger calls for innovative measures and visionary steps. Crop forecasting is useful with the availability of statistics that are utilised in planning, resource allocation, and policymaking for food deficits, as research conducted by Ramcharan et al. [2]. Agricultural farmers, government policymakers, and others involved in the agricultural sector, depending on which crops are more likely to be harvested in different regions of the country and at different times of the year, can take precautions to provide an uninterrupted supply of food and maximise the efficiency of the agricultural supply chain, efforts by Singh et al. [3].

Improvements in computer hardware, especially advanced machine learning technology, have made crop production forecasts much more precise. These technologies enable the manipulation of vast reservoirs of soil condition and weather pattern data for various crop types and past yields, as demonstrated by Arora [4]. Machine learning algorithms can reveal complex relationships and trends that are hard to identify with conventional methods. This information-driven model allows for improved, more accurate assessment of the variables that affect crop yields and conclusions that may be localised in terms of specific conditions of the farms or even a whole region. For example, machine learning algorithms can leverage different forms of information, e.g., soil water content, nutrient status, and pH level, which are important in making accurate predictions of crop growth, as conducted by Yang and Yu [5].

In the same way, climatic conditions—temperature fluctuation levels, precipitation intensities, moisture levels, and wind directions and velocities—also influence growth and development in crops. Previous experience yields records, including observations of different crops under various conditions, which are also covered in these models, as done by Botero-Valencia et al. [6]. Remote sensing technology and satellite imagery also provide other data layers that evaluate vegetation health, pest infestation, and other agronomics, providing a richer image of the agricultural environment. Integration of the various data sources is critical to the success of machine learning model prediction in crop yield estimation, as studied by Jeong [7]. Machine learning algorithms not only increase the precision of crop yield prediction but also provide valuable, actionable information to farmers.

Machine learning algorithms can suggest the best planting periods, crops to plant under specific conditions, and best irrigation cycles depending on weather conditions and soil type, as shown by Liu et al. [8]. Farmers of agricultural produce can subsequently utilise their information to make intelligent decisions regarding the optimal means of achieving their highest yield results with a reduction in wastage and inefficiencies. Although most regions of farmland worldwide are subjected to cumulative stresses caused by climate change, land erosion, and resource limitations, farmers are assisted by machine learning models that enable them to navigate challenging weather conditions and adopt more efficient agricultural practices. Its capacity to identify sustainable agricultural practices is among the major benefits of crop production forecasting using machine learning. These models can utilise data on resource consumption, i.e., water usage and fertiliser application rates, to suggest practices that enhance productivity while reducing environmental impacts, as suggested by Benos et al. [9]. For example, a machine learning model can suggest an irrigation practice that not only saves water but also returns the maximum yield from the crops for specific climate conditions. Besides, the models can propose intercropping or crop rotation methods that enhance long-term soil health, save chemical inputs, and support long-term agricultural sustainability, whose mission is executed by Benos et al. [9].

The capacity of machine learning algorithms to predict crop yields accurately also has far-reaching implications for food security planning and agricultural policy. Policymakers can utilise these predictions to design plans of sustainable agriculture, enhance resource redistribution and nutrition assistance, and establish safety nets to insulate farmers against potential food deficits, as utilised by Gao et al. [10]. A machine learning-based prediction, for instance, can identify zones of greater vulnerability to poor harvests in case of unfavourable weather, and governments can then target the distribution of relief, make investments in building infrastructure, or implement insurance plans for safeguarding farmers' earnings. These steps of prevention are all part of a stronger farm sector, one better able to deal with the uncertainty of an altered climate and volatile global food supplies, something that has been sought.

Beyond its meaning for local policymaking and agriculture, crop yield estimation through machine learning also has far-reaching implications for international trade and market stability. Commodity farming is highly internationally traded, and sudden supply changes lead to price volatility, impacting consumers and producers. Crop yield forecasts are early indicators of future shortages or surpluses of supply, enabling stakeholders to adjust and stabilise the markets, as noted by Sai Sharvesh et al. [11]. For instance, if a projection is made that the next season will be a bumper harvest in a given region, the government can pre-arrange storage, export planning, or marketing outlets. Alternatively, if a projection indicates reduced output, the government can increase imports, explore alternative food sources, or support local farmers in mitigating losses, as suggested by Sugiura [12].

As with increasingly advanced machine learning models, utility and accuracy improvements from the models can be even greater. Combined with recently developed technologies, such as advanced remote sensing technologies, the Internet of Things (IoT), and enhanced data-exchange architectures, these models can harvest more detailed data to forecast more effectively and tap into the data utilised by Archana and Sonkusare [13]. Their consistent improvement is the ongoing technique for creating such models with an endless loop of improving the method of forecasting to find more patterns within data, with the ability for ongoing innovation within forecasting in agriculture. Lastly, machine learning-conceptual crop production forecasting is imperative in a bid to ease the issues of feeding increasingly numerous mouths and still preserve the natural reserves in full, carried out by Zhai et al. [14]. By combining various datasets and sophisticated analysis methods, these projections provide information to guide decision-making that enables farmers to maximise practice, increase productivity, and enhance sustainability. The gains extend beyond the farm and affect policy development, market stability, and long-term food security planning. As machine learning technology continues to improve, there is an opportunity to achieve significant agricultural resiliency and efficiency, thereby meeting the world's food demand in a responsible manner, both environmentally and economically.

2. Literature Review

The researchers have applied emerging technologies like deep learning, machine learning, and Google Earth Engine to forecast wheat yield precisely, as carried out by Liu et al. [8]. It is a cross-disciplinary process where remote sensing data are integrated with advanced algorithms to build forecasting models that operate at both the county and the field levels. These methods not only enhance the precision of forecasting but also facilitate agricultural planning and management strategies that help policymakers and farmers make better decisions with the help of data and credible forecasts. The technology is of greatest benefit whenever farm systems are under stress due to increased world demands, unexpected climate trends, and environmental deterioration. The capacity to measure wheat yield with greater accuracy on a localised basis greatly improves resource allocation and management methodologies. These advancements are pivotal in improving farm productivity as well as reducing the wastage of resources in food crop production, research done by Jeong [7] has shown.

Ancillary research has also been carried out on how climatic factors control crop diversity in the case of a globally changing climate, research done by Gao et al. [10]. As climate change affects construction levels, it is essential to observe how climatic factors interact with agricultural yields so that food security for the future is ensured. Climatic predictors of crops are projected based on past weather observations, such as temperature, rainfall, and humidity, to comprehend the association. Knowing such patterns, scientists can empower policymakers, farmers, and researchers to formulate successful adaptation policies. Understanding how some climatic conditions influence crop growth at different stages of growth allows stakeholders to take proactive measures in mitigating the adverse impacts of climate change. The information enables farmers to adapt their methods to achieve high yields, regardless of changing environmental conditions, as demonstrated by research work conducted by Kamilaris and Prenafeta-Boldú [1].

Besides, information on the impacts of extreme climatic conditions such as droughts, floods, heatwaves, and storms on crops in farms is essential, as research applied by Ramcharan et al. [2]. Extreme weather conditions can devastate crops, resulting in significant yield losses, destruction, and poor-quality produce. Extreme weather conditions are worsening and becoming more frequent as a result of climate change, hence creating an additional priority on accurate prediction and control. By examining the history of climate and crop records, scientists can determine the frequency and magnitude of extreme events and their impact on agricultural production. This is how they're aware of sensitive crops and regions, and helps in developing sound agricultural production systems. It assists in developing predictive models for adverse weather conditions, enabling the establishment of pre-impact warning systems. This allows farmers and governments to react before any catastrophe, thereby reducing losses to crop yield and work done by Singh et al. [3].

Simultaneous studies have comprehensively examined the effect of heat stress on wheat yield, highlighting its significant impact on development, growth, yield, and quality, as noted in Arora [4]. Wheat, as the world's most significant staple cereal crop, is most vulnerable to the detrimental effects of heat stress, specifically the critical flowering and grain filling period. Wheat plant response at the physiological and biochemical level to a rise in temperature, i.e., alteration in photosynthesis, alteration in respiration, alteration in water uptake, and alteration in nutrient uptake, has been investigated in heat stress research, a study carried out by Yang and Yu [5]. Heat stress at these stages of critical development will inhibit growth and development in wheat plants on all fronts, with reduced yields and poor-quality grains. Identification of how the wheat crop could be rendered tolerant to heat at the cell level would result in the development of strategies for making this effect ineffective and the crops more heat-tolerant.

Various genetic and physiological heat tolerance traits of wheat, including heat shock proteins, antioxidants, and osmoprotectants, are employed by Botero-Valencia et al. [6] to function. These characteristics are most crucial in making wheat crops tolerant to the killing effect of heat stress. Wheat breeding for facilitating ownership of these characteristics is the most vital activity in creating heat-tolerant crop crops while maintaining yields despite hot temperatures. Genetic manipulation and biotechnology are also growingly central to developing heat-tolerant forms of wheat crops. By incorporating these traits into wheat crops, researchers aim to develop varieties that are more resilient to climate change stress, as demonstrated by Jeong [7].

Along with thermal tolerance breeding in wheat, management methods such as changing planting dates, irrigating to the maximum level, and shading or mulching to lower the temperature are in practice, as noted by Liu et al. [8]. All these processes, coupled with breeding, are maintaining the sustainability of wheat cultivation even in more intensifying weather conditions.

In the development of effective crop yield forecasting processes, researchers have adapted some very useful concepts from environmental characteristics, machine learning methods, and empirical studies, as utilised by Benos et al. [9]. The combination of environmental factors, such as land cover, topography, and hydrologic characteristics, with machine learning algorithms like gradient boosting and support vector machines has significantly enhanced the accuracy and applicability of crop yield prediction models, as demonstrated by research utilised in Gao et al. [10]. The machine learning models can handle complex data sets and identify patterns that other models cannot. Integration of such variables into model predictions makes it easier for farmers and researchers to make the predictions, which are highly specific to the region, cropping system, and climatic conditions, as studied by Sai Sharvesh et al. [11]. Even with the great progress made, there are a few challenges that still exist. It is most difficult to ensure data quality and continuity where there is extremely low technological infrastructure, as studied by Sugiura [12]. Representative and good-quality data for remote fields and geographies are vital in deriving accurate prediction models. Poor quality data translates into less predictable results, apart from a greater likelihood of mismanagement.

Additionally, precision and extrapolatability of the models continue to be difficult to attain, particularly in the regions that are subjected to severe climatic conditions or novel forms of environmental stresses. In such cases, machine learning models must be robust and adaptive in addressing the whimsical nature of volatile climates, as deployed by Archana and Sonkusare [13]. Seamless integration of data from various sources and the development of high-performance algorithms must offer this. The complex nature of machine learning models imposes a limitation on interpretability, which can disrupt stakeholders' understanding of how predictions are made, as evidenced by studies. Translucency of predictive models is required to gain the trust of farmers, policymakers, and other stakeholders. Machine learning models' interpretability techniques are required to provide increased user adoption and allow the models to function properly.

Furthermore, access and scalability are also central concerns because there are a rather large number of areas that lack the technologies to facilitate the utilisation of these systems, as implemented by Zhai et al. [14]. In overcoming such constraints, machine learning systems must be designed with fewer interfaces and integration options to facilitate easy adoption by farmers and other players in the agricultural industry. Ethics also feature in the design of crop prediction models. Justice, privacy, and information equity must be incorporated into decision-making to eradicate prejudice and unjustified assumptions. Allowing models to be constructed with a focus on helping all farmers, especially vulnerable members of society in communities who would disproportionately be adversely affected by agricultural conditions, is required, as work used by Kamilaris and Prenafeta-Boldú [1] suggests. This aims to address moral concerns, enabling forecasting systems to reach all stakeholders equitably, regardless of geography or socioeconomic status.

Technologically, predictive systems rely on a solid software and hardware foundation, a capability that has been successfully achieved by Benos et al. [9]. Python is primarily used as the basis programming language that Jupyter Notebook supports for debugging, and PyCharm is used as an integrated development environment, as demonstrated by Ramcharan et al. [2]. The basic libraries, such as Pandas for data manipulation, NumPy for numerical computation, Scikit-learn for training models, and TensorFlow or PyTorch for neural network modelling, are of utmost relevance to developing a crop forecasting system, efforts undertaken by Singh et al. [3]. Hardware configuration in terms of multi-core high-end CPUs and NVIDIA GPUs for heavy computation is also needed to handle big data and complex model training tasks, as utilised by Arora [4]. Apart from this, distributed computing environments like Apache Spark or Dask make it simpler to scale up for handling huge datasets, as carried out by Yang and Yu [5]. In general, despite improved crop yield prediction with the incorporation of machine learning and other newer technologies, model interpretability, data quality, scalability, and accessibility remain problems. However, these technologies have yet to be fully implemented to maximise the productivity of global agriculture and enhance resilience, thereby enabling improved adaptation to the effects of climate change and meeting global food supply requirements. By solving these problems and further refining these technologies, scientists can make crop yield forecasting systems more accurate, reliable, and equitable for all concerned, as efforts extended by Botero-Valencia et al. [6].

3. Methodology

To conduct an effective crop yield prediction analysis, one would require respective data sets from diverse sources. Such data sets would subsequently require processing in a specific way to meet the requirements of the model, and this might involve preprocessing and converting the data so that they have the desired attributes. The variables used in restoring the regression model include a list of major determinants of crop yield, such as weather, soil type, and quality, among others. Statistical models most often used in issues of prediction include regression analysis, since the outcome may be estimated based on independent variables that should impact the dependent variable. Regression analysis, in some instances, also identifies underlying relationships between independent and dependent variables, giving reflective information on crop production determinants.

Forecasts analysis to such an extent becomes essential in crop yield understanding and prediction, which continues to be essential in resource allocation as well as food security.

One of the principal problems in farm management is the allocation of land to crops, to permanent crops such as fruit trees, and temporary crops that are mostly annual or seasonal. Division can be made cumbersome, especially where there is intercropping. Temporary crops will likely find space in orchards until the permanent crops mature at the bearing stage. Temporary crops are subsequently seeded between the permanent crops. It is a highly accurate process, but one that requires determining and setting in advance how much space is devoted to each type of crop. It is the division that is most critical to maximising the utilisation of the land available and ensuring that the correct and proper cropping pattern is made. For example, in intercropping scenarios where different crops grow in separate rows, the coverage of each crop by the contributing crops can be estimated as a proportion of the rows occupied by those crops. The row ratio is calculated by dividing the rows in a line, whose length has been determined from three random locations. Dividing the number of average rows per crop allows us to calculate the relative area to be covered by each crop. This method keeps the intercropping system in a healthy balance such that every crop shall be allocated an equal share of resources like sunlight, water, and nutrients. Row intercropping is so widespread in use that it can maximise land use efficiency and enhance overall crop yield. Referring to the crop yield forecast system design, historical data as well as real-time data are included in the proposed approach to enhance the accuracy of predictions.

Weather, soil, cultivation practice, and crop type are all incorporated into the system. The system begins with large-scale data collection and preprocessing to clean the data and prepare it for use in training models. Raw data are preprocessed to efficiently extract features such as season-wise weather, measurements of soil fertility, and previous production. Building predictive models through machine learning with decision trees, random forests, and neural networks is done after preprocessing. The models can function fine with complex inter-variable relationships and are capable of making accurate predictions based on previous patterns. While developing the model, the hyperparameters of the system are defined in such a way that the model runs best. The performance of the model is afterwards measured by using common metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which are used to determine the measured crop yield versus actual crop yield. The loop is executed in such a way that the models are constantly updated for increased accuracy. Use of machine learning models enables the prediction system to improve over time with new information and become more accurate in making predictions. Apart from the main feature of crop yield prediction, the system also takes into consideration sustainability. Apart from the traditional variables that govern crop development, the system also incorporates sustainability variables such as water consumption, fertiliser consumption rates, and pesticide consumption rates. With such parameters in focus, the system not only provides accurate predictions but also maintains them.

Organic farming methods are becoming increasingly crucial as the agricultural sector must minimise its impact on nature. By considering these factors, the system can provide more accurate recommendations, enabling farmers to expand their operations while sustaining the environment. The system will subsequently become a decision-support system for both the policymakers and the farmers. Through the availability of these models with actionable inputs and recommendations from predictive models, the system allows stakeholders to make sound decisions on the use of resources and farming management. Forecasting enables the optimal use of resources such as water, fertilisers, and pesticides, thereby maximising crop production. Secondly, from the sustainability perspective, the system ensures the evolution of sustainable farming systems, which result in long-term sustainability and stability in food production systems. It is a principal source of driving force towards the making of agriculture efficient, sustainable, and responsive to climatic stresses.

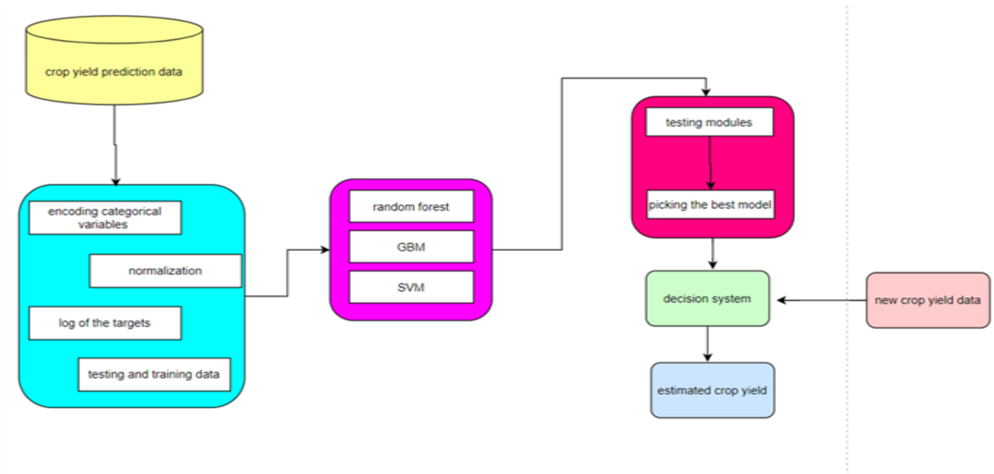

Figure 1: Crop yield prediction architecture

Figure 1 above illustrates the basic architecture of this project. System architecture illustrates the program flow to explain crop yield prediction. The program flow begins with the gathering of the dataset for crop yield prediction. Data fields are – month, weather, soil type, year, and used pesticides. Once the user's inputs are received, the model can forecast the crops that can be sown at the concerned location for higher yields. This model is implemented using Python IDLE to apply machine learning algorithms. Random forest is one of the machine learning algorithms used while designing this module. This classification ensemble employs a method called black bagging and applies a decision tree algorithm to build various decision trees. A Decision tree, which employs a tree-like model to represent decisions and their possible outcomes, is used. KNN: Offers higher accuracy when performance is considered, essentially recommending crops based on soil type and other factors.

All the data is fed through two stages: The training stage and the testing stage. Part of the data is given to the training stage, where the model is trained to deliver the correct output. In the training stage, various algorithms mentioned above are used to train the model. After the model is trained and accuracy is verified, the testing stage will be started. During the test phases, various inputs are given to train the data so that it produces the correct output. Depending on the information the model learned during the training phase, it will forecast the output. The model can also forecast various outputs, and the decision system will assist in selecting the optimum solution from these outputs and forecasting the output. Based on the acquired data, the model can provide estimated outputs regarding the crop yield in each season. Last but not least, the accuracy of the model is verified with various inputs.

The user accesses the system by creating different tasks, i.e., uploading a dataset with data of soil properties, crop properties, and other input variables. The system pre-processes the dataset by cleaning data, filling missing values, and normalizing it to prepare the data for analysis. Pre-processing is done to ensure data quality and preparedness for machine learning algorithms. The system then employs a sustainable crop yield prediction module based on machine learning, used to enable effective prediction of the crop yields in terms of sustainability. The module has various components, each contributing to the process. The pre-processing and data collection module is the first module, which collects various datasets like weather information, soil information, type of crop, history of yield records, satellite imagery, and agricultural practices.

The data is pre-processed to filter and clean it, making it ready for analysis at the time of collection and directly usable with machine learning models. The second module is feature engineering, which derives knowledge-rich features from processed data to improve model performance. This involves finding seasonal weather patterns, soil quality measurements, yield history patterns, and vegetation indices out of satellite images. More sophisticated feature engineering approaches are used to better represent features with good correlations to the data. The system proceeds to the model training and evaluation module, which performs machine learning model selection, training, and evaluation, such as decision trees, random forests, support vector machines (SVMs), or neural networks. Hyperparameters are optimised and performance improved when training models.

They are tested against accuracy metrics like Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Besides this, some other variables related to sustainability, such as land management, water consumption, rate of fertiliser, and rate of pesticide, are included in the prediction models for ensuring sustainability while predicting. These parameters in data pre-processing and model training are optimised for sustainability to make the best use of resources and reduce environmental effects. After training, the models become decision aids to farmers and policymakers in the decision-support module and deployment. The systems give advice and recommendations on anticipated yield and sustainability issues. Interactive interfaces and visualisation units are offered for presenting results in a consumable manner, such that stakeholders may make decisions depending on the usage of resources and agricultural practices. Concerning the features, the system has several principal components to preserve accuracy in the forecast, in addition to taking into account components of sustainability.

They consist of weather information (sun radiation, rainfall, wind speed, temperature, and humidity), soil information (organic matter percentage, soil water, nutrient status, and pH content), crop type information, year ago yield information, satellite image information for crop growth and crop disease management, and agricultural activity information such as pesticides application, crop rotation, and irrigation. Sustainability patterns of water usage, application of fertiliser, and land use in agriculture are also included, blended to offer green forecasts. Climatic patterns by seasons, soil health metrics, and phenology of plants, or an understanding of the stages of growth of crops, and in which of the four quarters of the year, in a quest to forecast variability in yields, are also considered by the system. By combining and computing these features and machine learning methods, the system constructs prediction models that create meaningful insights to improve resource optimisation, maximise the yield of crops, and improve environmental sustainability in agriculture. Figure 2 above is the core data flow of the project. Sustainable crop yield forecasting using machine learning is a task that needs a systematic data flow process. Initially, various datasets, such as weather, soil, crop, and historical data, are gathered. Thereafter, the data is pre-processed for cleaning and normalisation of data before analysis. Then, feature engineering harvests informative facts such as season-wise weather conditions and soil factors. Subsequently, machine learning models are trained on the pre-processed data to achieve maximum performance and generalisation. Trained models are then deployed into the production environment, ideally through cloud platforms, to ensure ease of use.

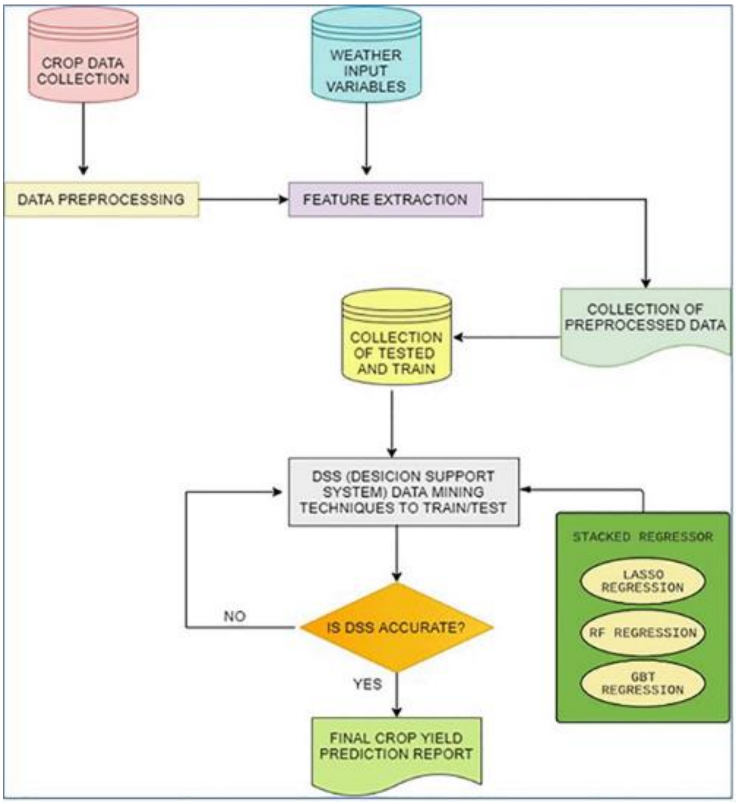

Figure 2: Sustainable crop yield prediction data flow

The farmers input real-time weather and soil data into the system, and predictions are made by the system based on various factors encompassing agricultural practices. These are presented in easily digestible formats to provide information and advice on effectively utilising resources and achieving high output sustainably. With this data-centric strategy, decision-makers can make informed choices to enhance farm productivity and maintain environmental balance. They will browse the song title or the singer's name to listen to songs, which will be held in the database. The admin can update or remove the song, which is also low-rated. The user can browse the song by singer/genre/writer/name, etc.

4. Results and Discussions

The study continues to show that weather has a great impact on crop yields because it makes farm production land and weather dependent. Sunlight radiation, temperature, rain, and wetness are weather conditions applied in crop development and growth planning. Bad weather, such as heat, drought, or floods, will negatively impact crop yield; therefore, studying weather conditions and prediction is important. Other than climate, physical properties of the soil, such as nutrient status, pH, texture, and water holding capacity, need to be planned in terms of crop productivity and health. Soil erosion, salinisation, degradation, and loss of nutrient status decrease crop yield and reduce crop activity; therefore, steps towards sustainable soil management are necessary.

Lastly, crop variety and genetics, which influenced their environmental adaptability, disease susceptibility, and capacity to produce, were of extremely important consideration. Enhanced crop improvement and recovery under high yield can be designed under plant breeding systems for stress resistance. Pest control and disease control were also of very high importance since IPM methods, such as resistance crop types and careful use of insecticides, reduced competition hazard from pests, diseases, and weeds to crops. The linear regression model for crop yield prediction is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ + \beta_n X_n + \varepsilon \qquad (1)$$

Where Y is the predicted crop yield, $X_1, X_2,$, X_n are the input features, β_0 is the intercept, $\beta_1, \beta_2, \ldots, \beta_n$ are the model coefficients, εis the error term.

Table 1: Sustainable crop yield prediction

Domain	Area	Element	Item	Year	Unit	Value
Crops	Afghanistan	Yield	Barley	1961	hg/ha	10800
Crops	Afghanistan	Yield	Barley	1962	hg/ha	10800
Crops	Afghanistan	Yield	Barley	1963	hg/ha	10800
Crops	Afghanistan	Yield	Barley	1964	hg/ha	10857
Crops	Afghanistan	Yield	Barley	1965	hg/ha	10857

There are statistics in Table 1 on the prediction of crop yield for the specific instance of Barley in Afghanistan during 1961-1965. There are columns like the Domain, which is given as “Crops,” and indicates that it is farm-related data. The Area column is for geographic area, and the Element column is for the kind of data, which is “Yield” here. The Item column is for crop, and it is Barley. The Year column is for years to which the data pertain, and the Unit column is for the fact that the yield is in hectograms per hectare (hg/ha). The Value column presents the actual yield values of Barley for these years, with all years reporting a similar yield of 10,800 kg/ha, and a slight increase in the last two years (1964 and 1965) to 10,857 kg/ha. Table 1 provides a snapshot of barley production consistency in Afghanistan over the past five years. Support Vector Machine (SVM) for the classification of yield levels will be:

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_L \, y_i K(x_i, x) + b\right) \qquad (2)$$

Where $f(x)$ is the decision function for classifying yield levels, α_i are Lagrange multipliers, y_i is the class label, $K(x_i, x)$ is the kernel function, b is the bias term.

Irrigation infrastructure and water supply were responsible for providing the right amount of moisture, especially in water-deficient or dry conditions. Crop density, application of fertilisers, rotation, and tillage practices are some of the crop management practices that all contribute in their way towards the yield of crops. Precision farm technology, best nutrient management, and timely farm operation were found to enhance yield and efficiency of the utilisation of resources. The economic considerations, i.e., farm policies, commodity prices, input prices, and market demand, were also seen to impact agricultural planning and crop yield forecasting.

The upcoming technologies, like satellite imagery, drones, remote sensing, and precision ag technology, provide higher accuracy along with timely estimation of crop yields to facilitate real-time decision-making and monitoring for the agriculture sector to flourish. Determinant geography and environment, like geographical location, elevation, slope, and proximity to a watercourse, were found to influence microclimates and croppability. Land use change and soil and air pollution were found to influence plant growth and crop health. Climatic change and climatic variability were found to be pervasive threats, including temperature alteration, shifts in rainfall patterns, and the onset of extreme weather events affecting crop yields (Figure 3).

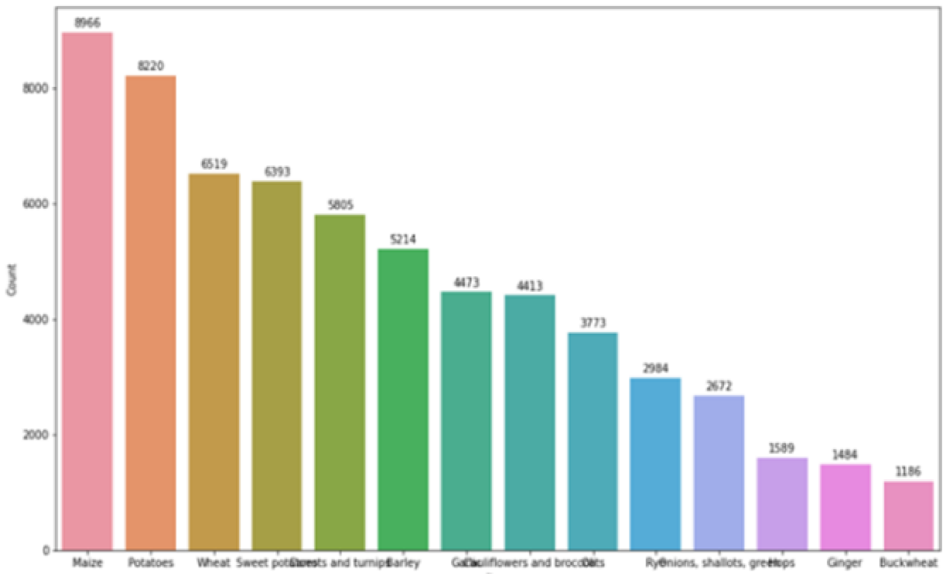

Figure 3: Representation of crop yield prediction

Random forest algorithm for regression is given below:

$$y = \sigma(\sum_{i=1}^{n} w_i \, x_i + b) \tag{3}$$

Where p is the predicted crop yield, $f_t(X)$ is the prediction from the t-th decision tree, T is the total number of trees in the forest. An artificial neural network for yield prediction is given by:

$$y = \sigma(\sum_{i=1}^{n} w_i \, x_i + b) \tag{4}$$

Where y is the output (predicted yield), x_i are the input features (e.g., rainfall, temperature), w_i are the weights associated with the input features, b is the bias term, and σ is the activation function.

The study highlighted the importance of building crop vulnerability to climate change and adaptation measures in an attempt to enhance sustainable food security. Under yield forecasting in the example, the study focused on area determination, where administrative or geographical areas whose yields had been previously estimated were predetermined, and regional mean yield estimates were computed. Machine learning models, such as regression analysis, decision trees, and neural networks, were utilised to achieve the highest prediction accuracy by identifying complex relationships between environmental factors and crop yield. Furthermore, ecologically friendly crop production yield models based on soil health indicators, biodiversity conservation, carbon sequestration, and water quality must be incorporated into the regenerative process of food production and environmental stewardship. There is a need to incorporate sustainability factors, such as fertiliser, pest control treatment, land practices, and water usage, into the crop yield projection model analysis.

Table 2: Data related to pesticide use in various countries

Domain	Area	Element	Item	Year	Unit	Value
Pesticides Use	Albania	Agricultural Use	Pesticides (total)	1990	tonnes	121
Pesticides Use	Albania	Agricultural Use	Pesticides (total)	1991	tonnes	121
Pesticides Use	Albania	Agricultural Use	Pesticides (total)	1992	tonnes	121
Pesticides Use	Albania	Agricultural Use	Pesticides (total)	1993	tonnes	121
Pesticides Use	Albania	Agricultural Use	Pesticides (total)	1994	tonnes	201
Pesticides Use	Zimbabwe	Agricultural Use	Pesticides (total)	2014	tonnes	2185
Pesticides Use	Zimbabwe	Agricultural Use	Pesticides (total)	2015	tonnes	2185
Pesticides Use	Zimbabwe	Agricultural Use	Pesticides (total)	2016	tonnes	2185
Pesticides Use	Zimbabwe	Agricultural Use	Pesticides (total)	2017	tonnes	2185
Pesticides Use	Zimbabwe	Agricultural Use	Pesticides (total)	2018	tonnes	2185

Table 2 shows the use of pesticides in Albania and Zimbabwe across various years. The information surrounds Agricultural Use of Pesticides, and it is quantified in terms of the total quantity of pesticides utilised in tonnes. The Domain is "Pesticides Use," i.e., the table 2 is centred on pesticide application rather than crop production. The Area column contains the countries, Albania and Zimbabwe. The Element column indicates the use type, which is agricultural, and the Item column to which the data pertain is all pesticides.

The Year column identifies the time frame covered by available data: 1990-1994 for Albania and 2014-2018 for Zimbabwe. The Value column provides the quantity of pesticides applied in tonnes, with a value of 121 tonnes for Albania over five years and a greater value of 2185 tonnes for Zimbabwe over 2014-2018. Table 2 provides the difference in pesticide application between the two nations over various time frames. Time-series forecasting using Autoregressive Integrated Moving Average (ARIMA) is:

$$Y_t = \mu + \sum_{i=1}^{p} \varphi_i \, Y_{f-i} + \sum_{j=1}^{q} \theta_j \, \varepsilon_{t^-j} + \varepsilon{:}_t \tag{5}$$

Where Y_t is the crop yield at time t, μ is a constant term, φ_i are the autoregressive parameters, θ_j are the moving average parameters, $\varepsilon{:}_t$ is the white noise error term at time t, p and q are the orders of the autoregressive and moving average terms, respectively.

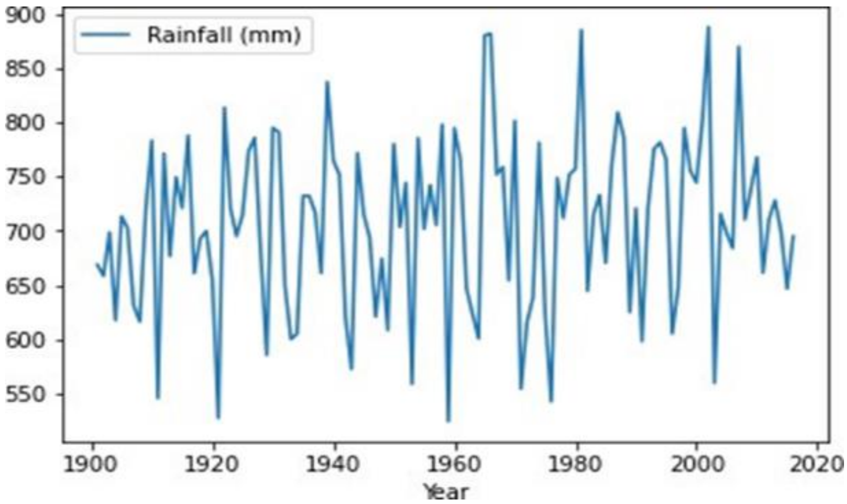

Figure 4: Time vs rainfall

Figure 4 is a rain time series graph (mm) from 1900 to 2020. The erratic pattern of rainfall is indicated by oscillations between 550 and 850 mm over decades. Oscillations are observed as variations in environmental or climatic terms over time, characterised by simple cycles of local peaks and troughs, which may indicate paired patterns of weather or precipitation over an extensive period. The overall trend does not seem to reflect a sudden increase or drop but rather oscillates, which symbolises cyclical change in rain during the previous century. The models study the yield, as well as offer decision-implementable counsel to farmers, agronomists, and authorities. They can include optimal planting dates, crop types, irrigation durations, fertiliser applications, and pest treatments, which return maximum yields while ensuring safety from environmental hazards.

The research found that to increase the prediction of sustainable crop yield and improve stress resistance of agriculture to the environment, data availability and model interpretability need to be addressed. Wastage avoidance, resource optimisation, and environmental footprint reduction in agriculture are achieved through predictive models that optimise productivity, profitability, and sustainability. These models will help decision-makers of stakeholders make well-informed decisions, ensuring agriculture remains compatible with long-term ecological balance and social health. It is thus imperative that crop yield forecasting models continually evolve in response to newer technologies, green technologies, and precise weather, soil, and crop data, ensuring agriculture becomes sustainable and robust under the conditions of global pressures like climate change.

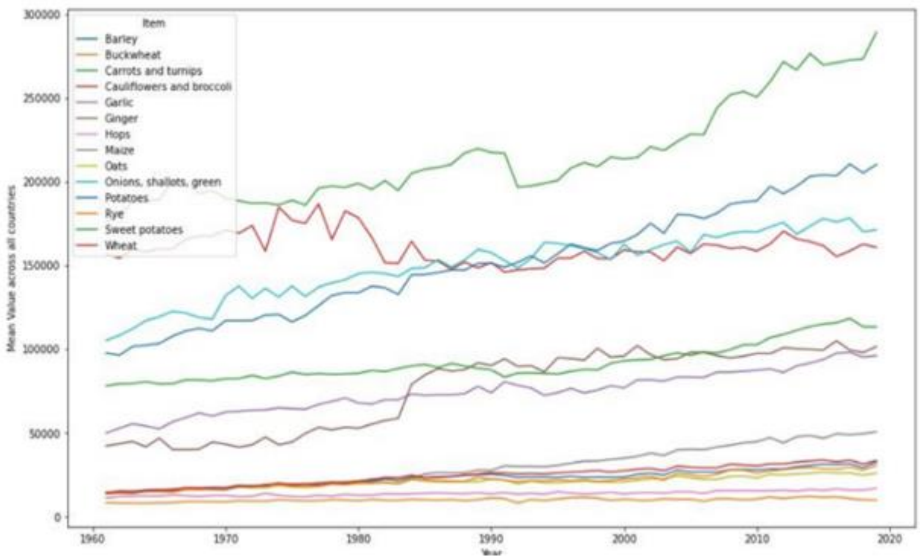

Figure 5: Mean value across all countries

Figure 5 is the average value of various crops for all countries between 1960 and 2020. The volatility and rise in the production value of Barley, wheat, maize, onions, and sweet potatoes are represented by the line graph. Rye and sweet potatoes mature slowly over time, but others, such as maize, wheat, and Barley, always mature early. The line indicates the pattern of the farm in yields as well as the various directions in the prices of the crops concerning the demand in the market, the weather, and agricultural mechanisation.

Table 3: Wheat production values in Zimbabwe over the period 2007-2016

Domain Code	Domain	Area Code	Area	Element Code	Element	Item Code	Item	Year Code	Year	Unit	Value
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2007	2007	hg/ha	29998
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2008	2008	hg/ha	30097
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2009	2009	hg/ha	30009
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2010	2010	hg/ha	27681
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2011	2011	hg/ha	26274
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2012	2012	hg/ha	24687
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2013	2013	hg/ha	22888
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2014	2014	hg/ha	21357
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2015	2015	hg/ha	19824
QC	Crops	181	Zimbabwe	5419	Yield	15	Wheat	2016	2016	hg/ha	18294

Table 3 provides the listed wheat production values in Zimbabwe over the period 2007-2016. It contains the Domain Code ("QC"), or the quality control portion of the data, and the Area Code (181), which defines Zimbabwe as the area of interest. Element Code (5419) and Item Code (15) define "Yield" and "Wheat" in the data. Year Code is the range of years for which data are available, from 2007 to 2016. Unit is being defined as "hg/ha" (hectograms per hectare), and the Value column is the annual wheat production in Zimbabwe. The figures demonstrate the volatility of wheat production, ranging from 29,998 hg/ha in 2007 to a low of 18,294 hg/ha in 2016, highlighting the volatility of wheat production over the period. This chart provides researchers and policymakers with both indexed and total figures, enabling anyone to analyse the trends in Zimbabwe's wheat production.

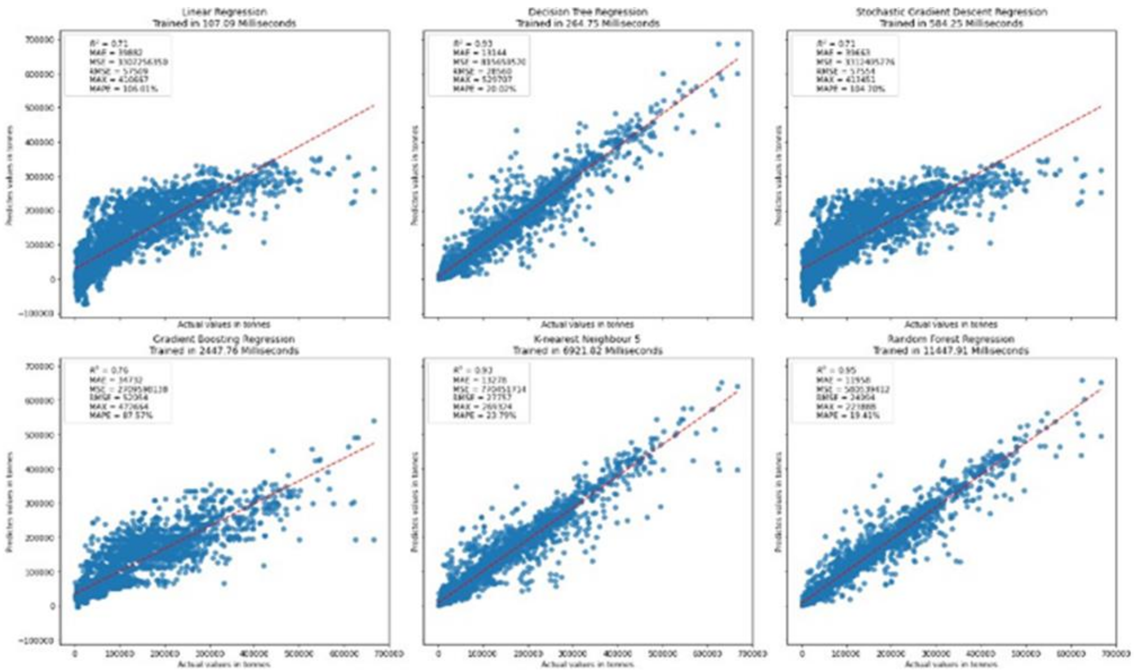

Figure 6: Algorithms used for crop yield estimation

Figure 6 shows six regression models to forecast the crop yield with scatter plots of predicted crop yield values and actual crop yield values in tons. The methods employed are Linear Regression, Decision Tree Regression, Stochastic Gradient Descent Regression, Gradient Boosting Regression, K-Nearest Neighbour 5, and Random Forest Regression. All the plots give the predicted vs. actual relationship, R^2, training time, and error metrics (MAE, MSE, etc.). Random Forest and Gradient Boosting models tend to give the best prediction with the highest R^2 and minimal scope for error, indicating they are best suited to estimate crop yield.

4.1. Discussions

The trends depicted by the tables and charts show significant trends in rainfall, pesticide application, and crop yield that are relevant to offer machine learning algorithms' ability to forecast sustainable crop yield. Figure 4 shows drastic changes in rainfall patterns year by year, corresponding to crop production. The 550 mm to 850 mm periodicity of rainfall from 1900 to 2020 indicates that the farm systems must be flexible in providing diversified weather conditions so that they can achieve productivity in the long run. This implies combining weather information with other agricultural variables for crop yield prediction. Machine learning algorithms, as shown in Figure 6, are highly applicable here. With climatic history of rain, temperature, etc., from the past, such algorithms can be tuned and can forecast the yield result regardless of natural fluctuations in weather.

The value increase of crops like Barley, wheat, and maize over time is also illustrated in Figure 5. Yield increase in these crops is mostly in line with the increase in farm technology, better agricultural practices, and maximum utilisation of resources. The trend suggests that, with the right predictive models, farm yields can be optimised by manipulating inputs such as pesticides, water, and fertiliser. Volatile demands for most commodities and intricate dynamics influencing crop harvests render the use of sophisticated machine learning algorithms imperative, as they can withstand these challenges. Regression models, as indicated in Figure 6, can best handle the complex relationship between input variables (e.g., fertiliser, pest control, and water usage) and crop yield, such that farmers can find out how to achieve optimum productivity.

Machine learning models employed to predict crop yield, as implied in Figure 6, are shown to predict crop yield with different levels of accuracy. For instance, the Random Forest Regression model can predict with 0.95 R^2 that it explains 95% of the variation in crop yields. Gradient Boosting Regression and K-Nearest Neighbour are also good performers, but less accurate than Random Forest. These models excel at identifying non-linear interrelations among farm data, such as those between climate, soil, crop, and pest management. The capacity of these models to process large datasets and learn from new data places them as important indicators of sustainable crop production, particularly under regimes of fluctuating environmental stress. Concerning the application of pesticides, as evident from Table 2, there is an increasing trend in the application of pesticides by countries such as Albania and Zimbabwe.

Altered agricultural practices, coupled with pest resistance, can plausibly account for these trends, and even stress to yield more in reaction to global food demands. Misuses of pesticide usage are, on the other hand, a massive environmental and health hazard, and sustainable crop yield prediction must factor in, therefore, as much as is feasible, not only maximum yield but environmental sustainability as well. Pesticide statistics and other crop and environmental parameters can be included in machine learning algorithms, whereby not just the yield of the crops is forecast. Still, even the most appropriate use of pesticides with less environmental damage is also forecast. The farmers establish all of these depending on such models for maximum productivity as well as the well-being of the environment.

Sustainable crop yield forecasting is also complex due to the differential yield of various crops in a region. For example, the yield of wheat in Zimbabwe for 2007-2016, as indicated by Table 3, shows a decreasing trend in wheat production. Yield reduced from 29,998 hg/ha to 18,294 hg/ha between 2007 and 2016. It may be due to soil erosion, water scarcity, or the inability to embrace technology. Machine learning algorithms can detect such trends and identify patterns that would help in the future to obtain more yields. For example, with the addition of satellite photography, soil condition tracking, and climatic trends, such algorithms can forecast the likely effect of varied agricultural practices on yield enhancement and recommend intervention to arrest declining trajectories in countries such as Zimbabwe.

Beyond precision in forecasting, applications of machine learning in sustainable agriculture lie in these models' ability to provide actionable recommendations regarding optimal utilisation of resources. For example, highly precise models such as Random Forest Regression for yield forecasting for plants may select major factors such as water, fertiliser, and soil, which contribute the most to yield. Farmers can streamline their practices more efficiently, lower costs, and increase output by focusing on the most crucial factors without degrading natural resources. This is even more so given the fact that operations of global agriculture must change towards sustainability in a bid to mitigate the threat of climate change, population increase, and resource shortages.

Additionally, the future of precision agriculture is highly promising. By feeding machine learning algorithms with Internet of Things (IoT) sensors, remote sensing, and Global Positioning Systems (GPS), highly advanced farming solutions can be rolled out. These technologies offer the farmer the option of monitoring crop health, level of soil moisture, temperature, and pest population numbers in real time, leaving him with information on which he can effectively and accurately act. By applying machine learning methods to this data, the farmer can predict potential yield loss and take necessary actions, thereby enhancing financial viability and profitability in their agriculture. In total, sustainable crop yield prediction with the help of machine learning models is an earnest attempt to solve the world's food production problems. With table and figure graphs, models can carry all kinds of high-order determinants of crop yield, from weather and pesticides to climatic variables and technology. Increased sophistication and maturity of this sort of algorithm, coupled with increased access to high-quality data, can allow farmers to be better supplied with what they require to obtain optimal production, make farming more sustainable, and construct food security in a more unpredictable future.

5. Conclusion

Briefly, machine learning-based sustainable crop yield forecasting is a revolutionary method that will transform agriculture today. With the integration of the strength of data analytics and better modelling, we can now forecast crop yields more precisely than ever before while keeping farming ecologically friendly. These climate forecasting models are ideal for efficiently utilising resources, such as water consumption and fertiliser application, while also reducing risks associated with climate variability and changing environmental conditions. The main benefit of using machine learning models to predict crop yields is that they can consider vast amounts of data from a wide variety of sources, from satellite photography to weather, soil content, and the history of yields. With all this information, such algorithms can identify complex patterns and relationships that might not be possible to identify in any other manner with traditional means of forecasting and thus make the forecasts for the yields sound and reliable.

Sustainable crop yield forecasting models also help farmers adopt environmentally friendly measures and enhance their resilience. For example, by isolating patches of water stress or nutrient inadequacies, these models may be able to facilitate successful irrigation and fertilisation schemes with less loss and more efficiency. Secondly, by utilising climatic fluctuation predicted as a response to yield fluctuation, growers can undertake preparatory measures, such as diversifying planting or shifting planting schedules, to avoid coupled loss. Interestingly, incorporating sustainability elements in our models guarantees that farm practices are in line with long-term ecosystem health and human well-being. By incorporating indicators for soil health, biodiversity conservation, and carbon sequestration in our model, we can determine interventions that can guarantee the health of farm ecosystems and farmers' well-being. As we strive to build our capacity and extend interdisciplinarity, machine learning and sustainability science provide an exciting vision for constructing innovation and resiliency in agriculture. By leveraging technology to deepen our understanding of the complex interplay between ecological systems and socioeconomic issues, we can create gateways to a more secure and sustainable future for our children and future generations.

5.1. Future Work

Future work in machine learning-based forecasting of future sustainable crop yield should aim to incorporate multi-source data fusion, like remote sensing images, IoT sensor measurements, and socioeconomic factors, to capture richer descriptions of the agriculture system. Adaptive dynamic modelling in real time, as a function of environmental and management fluctuations, will improve the quality of the forecast and allow for timely decisions. Climate change scenarios would be modelled under forecasting models to predict the effect of climate variability on crop yield, and policymakers can plan and act to prevent the threats. High-resolution spatial forecast models would be capable of predicting site-specific yields with local variations in soil properties, topography, and microclimates taken into account.

Ensemble learning methods, which combine the output of multiple models, improve accuracy by leveraging the strengths of various algorithms. Model interpretability and explainability will be enhanced, which will allow for end-user understanding and confidence and subsequently stakeholder decision-making. Incorporation of socioeconomic inputs like market prices, policy intervention, and supply of labour will allow for economic viability and sustainability of crop management plans. Lastly, the creation of user-friendly interfaces, user-friendly visualisation interfaces, and interactive dashboards will provide farmers and policymakers with predictive feedback. In brief, the application of new technologies, integration of heterogeneous data sources, and model explainability will lead to more intelligent and sustainable agriculture, resulting in accurate future crop yield predictions.

5.2. Limitations

The limitations of applying machine learning models to create precise, sustainable crop yield predictions are primarily in the data quality, availability, and complexity. The accurate forecasts are derived from a large database of high-quality datasets for different environmental, agronomic, and socioeconomic conditions. In most but not all locations, however, such synthesised datasets will not exist or be in short supply, restricting the usability and validity of the models. Machine learning algorithms are also processor- and data-intensive, and these could be in short supply in poorer environments. Algorithms can cope with many variables, but not always with the whole scope of climatic and ecological variables, especially if they are functioning in extreme or chaotic environments.

Additionally, most machine learning algorithms assume that past data patterns remain applicable in the future, but this is not always guaranteed when dealing with accumulating climate change or uncertain variables. Overfitting is also a problem that comes with this one, in which models trained on some data will not apply to other locations or environments. Lastly, machine learning model predictions will most likely be illegible, particularly by sophisticated deep learning models, and hence useless to decision-makers who require actionables. Hence, as better approximations for crop yield become feasible with the implementation of machine learning, practical utilisation is hindered by such issues and the need for ongoing optimisation and experimentation.

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References

1. A. Kamilaris and F. X. Prenafeta-Boldú, “Deep learning in agriculture: A survey,” *Comput. Electron. Agric.*, vol. 147, no. 4, pp. 70–90, 2018.
2. A. Ramcharan, K. Baranowski, P. McCloskey, B. Ahmed, J. Legg, D. P. Hughes, and L. Fei-Fei, “A machine learning approach to combined crop yield prediction and outlier detection: A case study in potato farming,” *PloS One*, vol. 8, no. 10, p. 1852, 2017.
3. A. Singh, B. Ganapathysubramanian, A. K. Singh, and S. Sarkar, “Machine learning for high-throughput stress phenotyping in plants,” *Trends Plant Sci.*, vol. 21, no. 2, pp. 110–124, 2016.
4. R. Arora, “Predicting crop yield using machine learning techniques: A survey,” *IEEE Access*, vol. 175, no. 1, p. 103326, 2021.
5. H. Yang and Y. Yu, “Sustainable crop yield prediction: A deep learning approach,” *in Proc. 23rd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, Elsevier, Netherlands, 2017.
6. J. Botero-Valencia, M. Mejia-Herrera, and J. M. Pearce, “Low cost climate station for smart agriculture applications with photovoltaic energy and wireless communication,” *HardwareX*, vol. 11, no. 4, p. e00296, 2022.
7. J. Jeong, “A review of crop yield prediction models based on machine learning techniques,” *Comput. Electron. Agric.*, vol. 163, no. 8, p. 104859, 2019.
8. J. Liu, K. Yang, A. Tariq, L. Lu, W. Soufan, and A. El Sabagh, “Interaction of climate, topography, and soil properties with cropland and cropping pattern using remote sensing data and machine learning methods,” *Egypt. J. Remote Sens. Space Sci.*, vol. 26, no. 3, pp. 415–426, 2023.
9. L. Benos, A. C. Tagarakis, G. Dolias, R. Berruto, D. Kateris, and D. Bochtis, “Machine learning in agriculture: A comprehensive review,” *Sensors*, vol. 21, no. 11, pp. 1–55, 2021.
10. L. Gao, J. An, S. Chen, and Y. Zhang, “Crop yield prediction using machine learning techniques: A comprehensive review,” *Comput. Electron. Agric.*, Elsevier, Netherlands, 2020.
11. R. Sai Sharvesh, K. Suresh Kumar, and C. J. Raman, “An accurate plant disease detection technique using machine learning,” *EAI Endorsed Trans. Internet Things*, vol. 10, no. 1, pp. 1–9, 2024.
12. R. Sugiura, “Deep learning-based crop yield prediction using remotely sensed data and crop phenology,” *Remote Sens.*, vol. 12, no. 17, p. 2745, 2020.
13. S. Archana and S. Sonkusare, “A comprehensive survey on crop yield prediction techniques,” *Neural*, vol. 22, no. 2, pp. 579–592, 2023.
14. Y. Zhai, Z. Wen, Y. Xia, P. Li, and S. Li, “Crop yield prediction using deep learning: A review,” *Comput. Electron. Agric.*, vol. 10, no. 5, pp. 1–11, 2020.