

# Weather and Crop Yield Prediction by Machine Learning Model and Spiking Neural Network

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## ABSTRACT:

This paper, "Weather and Crop Yield Prediction by Machine Learning Model and Spiking Neural Network," is to improve crop yield prediction efficiency by utilizing cutting-edge technology and transform agricultural practices. The creation of two prediction models specifically for this purpose is the main goal of the study. The first model incorporates geographical information such as Normalized difference vegetation index (NDVI), Standard Precipitation Index (SPI), and Vector Choquet Integral (VCI) and uses a Genetic Algorithm to reduce the size of the input dataset. This reduction attempts to lessen learning process confusion brought on by comparable data with different values. The model improves its capacity to identify pertinent patterns for precise yield estimates by incorporating spatial data. The SoftMax function is employed by the second model, a Modified Convolutional Neural Network (MCNN), as an error correcting method. By reducing errors and raising the overall accuracy of the model, the SoftMax function improves the output and produces forecasts that are more accurate. The study emphasizes how crucial geographic data including satellite imagery is for supplying crucial insights for predicting crop yields. Farmers can make well-informed decisions by having a thorough understanding of agricultural dynamics, which is facilitated by spatial patterns and temporal shifts. Statistical and geographic data are used to completely study the effects of numerous variables, such as biological, economic, and environmental ones, on crop yield production. The goal of the project is to create precise and effective instruments that enable farmers to make knowledgeable decisions about their soil by combining machine learning with spiking neural networks.

**KEYWORDS:** Crop yield prediction, Machine learning, Spiking neural network, Geographical Information, Genetic Algorithm, SoftMax Function, Agricultural dynamics

## INTRODUCTION

In the realm of agriculture, accurate predictions regarding weather patterns and crop yields hold paramount importance. The ability to forecast weather conditions and crop production outcomes plays a pivotal role in shaping agricultural practices, informing decision-making processes, and ultimately ensuring food security on a global scale. In this section, we will delve into the significance of accurate weather and crop yield prediction, the challenges encountered by farmers and policymakers, and the role of artificial intelligence (AI) and machine learning (ML), specifically neural networks, in mitigating these challenges. Weather fluctuations and their subsequent impact on crop yields are intricately linked phenomena that significantly influence agricultural productivity and food availability. Accurate weather predictions empower farmers to make informed decisions regarding planting schedules, irrigation practices, pest

management strategies, and harvesting timelines. By anticipating weather-related risks such as droughts, floods, heatwaves, and storms, farmers can adopt proactive measures to safeguard their crops and minimize potential losses. Additionally, precise forecasts enable policymakers to formulate effective agricultural policies, allocate resources efficiently, and mitigate the adverse effects of climate variability on food production.

Moreover, reliable predictions of crop yields are indispensable for optimizing resource allocation, enhancing supply chain management, and ensuring market stability. By anticipating variations in crop output, stakeholders across the agricultural value chain can streamline distribution channels, manage inventory levels, and plan marketing strategies accordingly. Furthermore, accurate crop yield forecasts facilitate risk assessment and financial planning for farmers, lending institutions, and insurance providers. Overall, the ability to forecast weather patterns and crop yields with precision is instrumental in promoting agricultural sustainability, economic resilience, and food security worldwide.

### **Challenges Faced by Farmers and Policymakers:**

Despite the critical importance of weather and crop yield prediction, farmers and policymakers encounter numerous challenges in accurately forecasting these variables. One of the primary challenges stems from the inherent unpredictability of weather patterns, which are influenced by a myriad of factors such as atmospheric conditions, ocean currents, and geographic features. Variability in climate phenomena, including El Niño, La Niña, and the North Atlantic Oscillation, further complicates forecasting efforts, leading to uncertainties in precipitation, temperature, and humidity levels.

The dynamic nature of agricultural systems introduces complexities that pose challenges for crop yield prediction. Factors such as soil quality, nutrient availability, pest infestations, and crop diseases interact in intricate ways, making it challenging to model and predict crop production outcomes accurately. Moreover, socioeconomic factors such as market demand, trade policies, and labor availability add another layer of complexity to the forecasting process, influencing planting decisions, yield projections, and market prices. Furthermore, traditional forecasting methods often rely on simplistic statistical models that fail to capture the nonlinear relationships and complex interactions inherent in weather and crop systems. These models may overlook critical variables, underestimate uncertainty, and yield inaccurate predictions, thereby limiting their practical utility for farmers and policymakers alike. As a result, there is a pressing need for advanced predictive analytics techniques that can effectively harness the wealth of available data and provide reliable forecasts for weather and crop yields.

### **Role of Artificial Intelligence and Machine Learning:**

In recent years, artificial intelligence and machine learning have emerged as powerful tools for addressing the challenges associated with weather and crop yield prediction. Unlike traditional statistical methods, which rely on predefined assumptions and linear models, AI and ML techniques, particularly neural networks, offer a data-driven approach that can uncover hidden patterns, identify complex relationships, and adapt to changing conditions. Neural networks, inspired by the structure and function of the human brain, excel at processing vast amounts of data, learning from examples, and making predictions with remarkable accuracy. By leveraging large datasets containing meteorological variables, soil properties, historical yield data, and agronomic practices, neural networks can generate forecasts for weather patterns and crop yields with unprecedented precision. The ability of neural networks to capture nonlinear interactions, generalize patterns across different geographical regions, and adapt to evolving

environmental conditions makes them well-suited for agricultural prediction tasks. Moreover, the integration of AI and ML techniques into weather and crop yield prediction models enables continuous learning and refinement, allowing these models to improve over time and adapt to changing scenarios. By incorporating real-time observations from weather stations, satellites, and remote sensing technologies, neural networks can provide up-to-date forecasts that are essential for timely decision-making in agriculture. Artificial intelligence and machine learning, particularly neural networks, hold immense promise for revolutionizing weather and crop yield prediction in agriculture. By addressing the challenges of uncertainty, complexity, and variability inherent in weather and crop systems, these advanced techniques can empower farmers, policymakers, and other stakeholders with actionable insights that contribute to agricultural sustainability, economic stability, and food security. In the following sections, we will delve deeper into the applications, methodologies, and case studies that illustrate the transformative potential of AI and ML in weather and crop yield prediction.

### **Weather Prediction with Neural Networks:**

Weather prediction is a critical aspect of agriculture and various other industries, influencing decision-making processes, resource allocation, and risk management strategies. Neural networks have emerged as powerful tools for weather forecasting, leveraging large datasets of meteorological information to generate accurate predictions of various weather phenomena. In this section, we will explore how neural networks integrate meteorological data to forecast weather phenomena such as temperature, precipitation, humidity, wind speed, and atmospheric pressure. Neural networks integrate diverse meteorological data sources to forecast weather phenomena accurately. These data sources include historical weather observations, satellite imagery, radar data, atmospheric models, and remote sensing technologies. Each data source provides valuable information about different aspects of the atmosphere, allowing neural networks to capture the complex interactions and dynamics that influence weather patterns. For example, historical weather observations contain information about past weather conditions, allowing neural networks to identify trends and patterns over time. Satellite imagery provides real-time information about cloud cover, precipitation, and atmospheric circulation patterns, enabling neural networks to track weather systems and predict their movement. Radar data offer insights into precipitation intensity and storm development, helping neural networks forecast rainfall and severe weather events. Atmospheric models simulate the behavior of the atmosphere based on physical principles, providing additional input for neural network forecasts. Remote sensing technologies, such as lidar and microwave sensors, measure atmospheric properties such as temperature, humidity, and air pressure, enhancing the accuracy of weather predictions. By integrating these diverse data sources, neural networks can generate comprehensive forecasts of various weather phenomena, enabling stakeholders to make informed decisions and mitigate risks associated with weather variability.

### **Training Neural Networks for Weather Prediction:**

Training neural networks for weather prediction involves several steps, including data preprocessing, model selection, and evaluation metrics. Before training a neural network, meteorological data must be preprocessed to ensure compatibility with the network architecture and optimization algorithms. This may involve data normalization, feature scaling, missing data imputation, and temporal aggregation. Normalization ensures that input features have similar ranges and distributions, preventing large gradients and unstable training behavior. Feature scaling adjusts the magnitude of input features to improve

convergence and stability during training. Missing data imputation replaces missing values with estimated values based on neighboring observations or interpolation techniques. Temporal aggregation aggregates temporal data into fixed intervals (e.g., hourly, daily) to reduce computational complexity and improve generalization.

### **Model Selection:**

Choosing an appropriate neural network architecture is crucial for weather prediction tasks. Various architectures, including feedforward networks, recurrent neural networks (RNNs), convolutional neural networks (CNNs), and deep learning models, have been used for weather forecasting. Feedforward networks are suitable for modelling static relationships between input and output variables. RNNs are well-suited for sequential data processing, making them ideal for time-series forecasting tasks. CNNs excel at capturing spatial patterns in data, such as satellite imagery and radar data. Deep learning models, such as long short-term memory (LSTM) networks and gated recurrent units (GRUs), combine the strengths of RNNs and CNNs, allowing them to capture both temporal and spatial dependencies in meteorological data.

### **Evaluation Metrics:**

Evaluating the performance of a neural network model requires the selection of appropriate evaluation metrics. Common metrics for weather prediction tasks include mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R-squared). MAE measures the average absolute difference between predicted and observed values, providing a measure of prediction accuracy. MSE and RMSE quantify the average squared difference between predicted and observed values, penalizing large errors more heavily. R-squared measures the proportion of variance explained by the model relative to the total variance in the data, indicating the goodness of fit. Numerous case studies and examples demonstrate the application of neural networks in weather forecasting at different spatial and temporal scales. For instance, researchers have used neural networks to predict temperature, precipitation, and wind speed at local, regional, and global scales, achieving high levels of accuracy and reliability. In addition, neural networks have been applied to specific weather phenomena such as hurricanes, tornadoes, and heatwaves, providing early warning systems and risk assessment tools for stakeholders. One notable example is the use of deep learning models to forecast extreme weather events, such as hurricanes and typhoons. By analyzing historical weather data and incorporating real-time observations from weather stations and satellites, researchers have developed neural network models capable of predicting the intensity, track, and landfall of tropical cyclones with unprecedented accuracy. These models enable policymakers, emergency responders, and the public to prepare for and mitigate the impacts of severe weather events, reducing the loss of life and property damage. Another example is the application of neural networks to predict localized weather phenomena, such as thunderstorms and flash floods. By combining radar data, satellite imagery, and ground-based observations, researchers have trained neural network models to identify convective cells, track storm motion, and estimate rainfall intensity in real-time. These models provide valuable information for weather forecasting agencies, emergency management organizations, and infrastructure operators, enabling them to issue timely warnings and implement mitigation measures to protect lives and property.

**Crop Yield Prediction with Neural Networks:**

Crop yield prediction is a complex and multifaceted task that requires comprehensive understanding of the factors influencing crop growth, development, and productivity. In this section, we will investigate the factors influencing crop yield prediction, explore how neural networks leverage diverse datasets to predict crop yields, discuss the challenges and limitations associated with crop yield prediction using neural networks, and present case studies and research findings illustrating the effectiveness of neural networks in predicting crop yields across different crops and regions.

**Factors Influencing Crop Yield Prediction:**

Crop yield prediction is influenced by various factors, including soil characteristics, climate conditions, crop genetics, management practices, and socioeconomic factors.

**Soil Characteristics:**

Soil properties such as texture, fertility, moisture content, and nutrient availability play a significant role in determining crop yields. Different soil types have distinct water-holding capacities, drainage characteristics, and nutrient retention capacities, affecting plant growth and productivity. Soil fertility, determined by factors such as organic matter content, pH, and nutrient levels, influences nutrient uptake, root development, and crop yield potential. Soil moisture content affects plant water availability, root growth, and nutrient transport, impacting crop growth and development. Soil compaction, erosion, and salinity can also affect crop yields by reducing root penetration, nutrient uptake, and water infiltration rates.

**Climate Conditions:**

Climate factors such as temperature, precipitation, sunlight, and humidity significantly influence crop growth, development, and yield outcomes. Temperature affects crop phenology, photosynthesis, respiration, and reproductive processes, influencing growth rates, flowering times, and yield formation. Precipitation provides water for plant growth and regulates soil moisture availability, affecting crop water stress, root development, and yield potential. Sunlight is essential for photosynthesis, providing energy for plant growth, biomass accumulation, and yield formation. Humidity influences transpiration rates, leaf stomatal conductance, and plant water balance, affecting crop water stress, nutrient uptake, and yield formation.

**Crop Genetics:**

Crop genetics plays a crucial role in determining yield potential, resilience to environmental stresses, and agronomic traits such as yield stability, maturity duration, and disease resistance. Different crop varieties exhibit varying levels of yield potential, adaptability to local growing conditions, and resistance to biotic and abiotic stresses. Plant breeding programs aim to develop new crop varieties with desirable traits such as high yield potential, uniform maturity, stress tolerance, and nutritional quality. Genetic diversity within crop species enables farmers to select varieties suitable for their specific growing conditions, management practices, and market preferences.

**Management Practices:**

Agronomic practices such as planting density, crop rotation, irrigation, fertilization, pest control, and

harvesting techniques significantly influence crop yields. Planting density affects crop competition for light, water, and nutrients, influencing individual plant growth rates, biomass accumulation, and yield potential. Crop rotation improves soil fertility, reduces pest pressure, and breaks disease cycles, enhancing crop health and productivity. Irrigation provides supplemental water during dry periods, mitigating drought stress and ensuring optimal crop growth and development. Fertilization supplies essential nutrients such as nitrogen, phosphorus, and potassium, supporting plant growth, reproduction, and yield formation. Pest control measures such as integrated pest management (IPM) strategies, biological control agents, and chemical pesticides protect crops from insect pests, diseases, and weeds and minimizing yield losses.

## **LITERATURE SURVEY:**

### **Climate Prediction Models:**

Climate prediction models are commonly created by climate research institutes and meteorological agencies. They use complex numerical simulations to anticipate future global and regional climatic conditions. These models mimic the behavior of the Earth's atmosphere, seas, land surfaces, and ice cover by combining intricate mathematical algorithms with fundamental physical concepts. Understanding long-term climate trends and patterns is essential for comprehending the possible effects of climate change on ecosystems, agriculture, water resources, and human societies. This is one of the main goals of climate models. Climate models assist academics, stakeholders, and policymakers in making well-informed decisions on mitigation and adaptation measures by modelling various scenarios of greenhouse gas emissions and evaluating their effects. One of the primary purposes of climate models is to provide insights into long-term climate trends and patterns, which are crucial for understanding the potential impacts of climate change on ecosystems, agriculture, water resources, and human societies. By simulating different greenhouse gas emission scenarios and assessing their consequences, climate models help policymakers, researchers, and stakeholders make informed decisions about mitigation and adaptation strategies.[1]

### **Crop Modelling Software:**

The term "crop modelling software" describes a group of computer-based instruments that mimic the growth and development of crops under various environmental circumstances by using complex mathematical formulas and algorithms. To forecast agricultural yield outcomes, these software programs combine data on a variety of variables, including temperature, precipitation, solar radiation, soil properties and crop genetics.

These software programs' underlying crop models are usually derived from accepted scientific theories and empirical information gathered from field research and observations. The physiological processes involved in plant growth, such as photosynthesis, respiration, transpiration, nutrient intake, and biomass buildup, are captured in these models.

Through the input of environmental data and management strategies, users can model the response and growth of crops over time. With crop modelling software, users can experiment with different planting dates, irrigation schedules, fertilizer application rates, and crop kinds to investigate "what-if" possibilities. This facilitates the assessment of various management approaches and their possible effects on agricultural yield, resource efficiency, and climate variability resilience by farmers, researchers, and policymakers. Because crop modelling software offers useful insights into the intricate relationships between crops, soils, and climate, it is an essential tool for agricultural decision-making. By using these technologies, farmers

can increase food security, optimize agricultural techniques, manage resources better, and reduce risks related to climatic unpredictability.[2]

**PROPOSED SYSTEM:**

In order to improve the precision and effectiveness of crop production predictions, the suggested method, "Weather and Crop Yield Prediction by Machine Learning Model and Spiking Neural Network," presents novel techniques. Key elements like they suggested system are as follows

Enhanced Integration of Data and Sources of Data makes use of a variety of data sources, such as satellite-based remote sensing data, the Normalized Difference Vegetation Index (NDVI), the Standard Precipitation Index (SPI), and the Vegetation Condition Index (VCI). The goal of integrating such extensive temporal and spatial data is to obtain a more comprehensive picture of environmental conditions.

**Genetic Data Reduction Algorithm:**

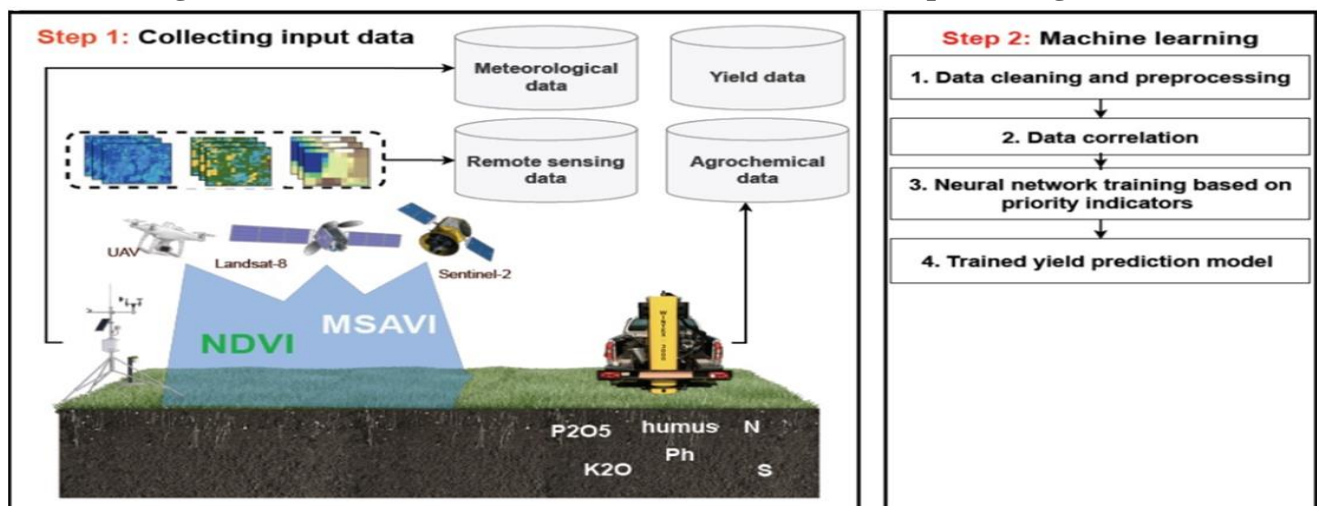
Uses a genetic algorithm to minimize the input data's complexity. Aims to reduce confusion during the learning process caused by redundant or similar data by streamlining the dataset by concentrating on important geographical information.

**Modified Convolutional Neural Net (MCNN):**

Makes use of an MCNN that has been Modified to incorporate the SoftMax function. This method introduces the SoftMax function as an error correcting strategy to improve forecast accuracy. The MCNN's ability to identify spatial patterns and correlations in the input data can help forecast agricultural yields with greater accuracy. Constructs a Spiking Neural Network (SNN) by integrating it into the modelling framework. Makes use of SNNs' ability to replicate neural communication patterns in the brain in order to improve our comprehension of the intricate relationships and temporal dynamics that exist within agricultural systems. The purpose of the Decision Support System for Farmers is to provide farmers with precise and effective instruments for making decisions.

Dynamic modelling is intended to be flexible in response to shifting circumstances and to continuously learn from fresh data. As more data becomes available, the system can adapt over time, adding new insights and making better predictions.

**Figure 1: Data Collection Method For Weather And Crop Yielding Prediction**



**Table 1: Comparison on Existing System and proposed system**

CONTENT	EXISTING SYSTEM	PROPOSED SYSTEM
Data Sources	Often rely on satellite-based remote sensing and meteorological data to provide information on weather conditions and environmental factors.	Incorporates advanced data sources, including NDVI, SPI, and VCI, alongside satellite data, to enhance the spatial and temporal resolution for more accurate predictions.
Modelling Techniques	May use traditional statistical methods or crop modeling based on mathematical equations.	Utilizes advanced machine learning models, including a Modified Convolutional Neural Net (MCNN) with the SoftMax function, and Spiking Neural Network for improved accuracy in predicting crop yields.
Complexity of Models	Models may be simpler, focusing on basic correlations between weather variables and crop yields.	Incorporates sophisticated techniques such as Genetic Algorithms and a Modified Convolutional Neural Net, introducing complexity to the models for a more nuanced understanding of the data
Decision Support	Often provide decision support for farmers based on historical data and basic predictions	Aims to empower farmers with more accurate and efficient tools for decision-making by leveraging advanced machine learning techniques.
Temporal Aspect	Typically focus on short to medium-term weather predictions	Incorporates temporal changes and dynamic patterns, recognizing the importance of understanding agricultural dynamics over time.

**CONCLUSION:**

In conclusion, the suggested approach combines sophisticated machine learning models, a Spiking Neural Network, and extensive data sources in an effort to push the limits of agricultural output prediction. The



intention is to give farmers an effective instrument for risk mitigation and well-informed decision-making in the dynamic and intricate field of agriculture. the integrated approach combining weather data and machine learning techniques offers a promising solution for improving crop yield prediction accuracy. By accurately forecasting crop yields, farmers can optimize agricultural practices, mitigate risks associated with weather variability, and enhance overall productivity. Future research directions may involve refining the prediction model, incorporating additional variables such as soil characteristics and pest/disease prevalence, and developing user-friendly tools for farmers to access and utilize the predictions effectively. Overall, this study contributes to the advancement of agricultural science and provides valuable insights for sustainable farming practices.

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