

P-ISSN: 2706-7483
E-ISSN: 2706-7491
NAAS Rating: 4.5
IJGGE 2025; 7(3): 38-45
www.geojournal.net
Received: 19-01-2025
Accepted: 24-02-2025

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AI-enhanced climate adaptation strategies for smallholder farmers in a warming world

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DOI: <https://www.doi.org/10.22271/27067483.2025.v7.i3a.352>

Abstract

This research investigates the potential of AI-enhanced climate adaptation strategies for smallholder farmers in the context of global warming. Climate change is increasing in intensity and smallholder farmers are struggling as they face price volatility, unemployment, crop failure and increasingly scarce natural resources in many places. It investigates the use of “support vector machines (SVM), random forests (RF), artificial neural networks (ANN) and k nearest neighbor (KNN) type of AI algorithms for enhancing farming practices and for making them more resilient to climate change.” These algorithms were evaluated in terms of how well they could predict crop yields, optimize irrigation, and detect pests by using data from real time environmental sensors, weather forecasts, and crop performance indicators. ANN performed the best as it had a yield prediction accuracy of 92.4%, followed by RF, SVM with 89.7%, 85.6% respectively and then KNN with 82.1%. AI integration with IoT devices for actionable insights offered the farmers a chance to make informed decisions, resulting in water use efficiency improved by 15% and crop yields by 10%. The use of AI as a tool to support sustainable farming and climate resilience for smallholder farmers, and particularly for small holder farmers living in low income countries is demonstrated.

Keywords: AI, climate adaptation, smallholder farmers, machine learning, agriculture sustainability

Introduction

Smallholder farmers in developing regions are among those most threatened by the effects of climate change due to the fact that agriculture is the main source of their lives. The costs of the conventional farming are rising due to climate change and the extreme climatic events that occur along with them like droughts and floods that arise from extraordinary rise in temperatures and unpredictable weather pattern. Smallholder farmers of these environmental changes are many of the most vulnerable, but rarely have the resources and infrastructures necessary to adapt ^[1]. This has resulted in an emergency for inventions that can help these farmers should they survive the effects of climate change or not to be caught by events, so to speak, of the future. It is important to note that Artificial Intelligence (AI) has a transformative ability to get over these problems ^[2]. AI can help unlock data driven insights to optimize crop management, water use, pest control, to enhance farm productivity for farmers. Real time, location specific recommendations can be provided by such machine learning, predictive analytics and Internet of Things (IoT) enabled sensors and will help in making decision making process easier in farming operation ^[3]. AI based systems can also assist us in making long term modeling of what is going to be the weather tomorrow and when the farmers can consultancy to predict what the weather to be like one period and plan for subsequent weather pattern. The aim of this research is to explore the possibilities for AI enhanced climate adaptation strategies for the smallholder farmers. It looks at how these technologies can be applied within existing agricultural systems in order to reduce climate risk and improve resilience. This study seeks to use AI in order to support smallholder farmers in the context of climate change in a cost effective, scalable and sustainable way. In the end, it's about giving farmers the means to respond to a warming world and to keep food in the bowl and people in the fields for the next generations.

Related works

For a brief period, integrating Artificial Intelligence (AI) to agriculture especially smallholder's farm has obtained great interest. A very interesting finding is the potential of AI to tackle climate change challenges and to improve the farming practices in the low

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income countries. AI has been applied to a range of climate adaptation strategies; specifically, to determine how to optimize agricultural practices, improve prediction of crop yield, and promote sustainable farming systems.

AI in low income countries: Khan *et al.* [15] explored the usage of AI in the low income countries and how the application of AI technologies is expected to assist improve the agricultural productivity. The study focused on how AI could be used to optimize the use of resources, predict weather patterns, and increasing the crop's resistance to climatic stresses. What's more, this is relevant especially for smallholders that have limited resources and face growing volatility in their climate conditions.

An area of interest by Mahmud *et al.* [16] was the problem of weedy rice infestation in Malaysia, a perennial problem for the smallholder farmer. And the study looked at AI solutions for early detection, control of weed infestations, which would be a great factor in rice production. First, the authors showed how farmers can quickly identify weeds and take timely action, thereby minimizing crop loss and the ultimate food security problems. The importance of AI for pest and weed management fits well with the rise of interest in AI's role in tackling climate adaptation in agriculture. Specifically, Miller *et al.* [17] employed AI agents with the Internet of Things (IoT) for improved environmental sensing, particularly relating to water quality and climate data. This was a study that outlined how natural resource management could leverage the work of real time environmental data using AI models to craft actionable intelligence. Such AI IoT integrations can benefit smallholder farmers through gaining real time weather information, soil moisture data and many relevant agricultural metrics that would help the farmers make better informed decisions and boost their productivity in a changing climate.

AI has been applied in real-time contamination classification in grapes using an IoT enabled devices, by Mohammed *et al.* [18]. As this study was centered on the production of grapes, there are some important reflections for the usage of AI in agriculture. Real-time monitoring using AI-enhanced IoT gives farmers an opportunity to react immediately on climate related events like extreme weather or pest infestations, which can contaminate or loose the crop. Such technologies are adaptable to smallholder farms to increase their climate resilience and food safety standards.

In the case of arising economies, the role of AI in achieving a net zero carbon economy have been examined by Mondal *et al.* [19] regarding digital inclusion and climate resilience. PLS SEM and fsQCA approaches were applied to the study to examine the relationship between AI adoption and climate goals. The study pinpointed AI's potential for smallholder farmers to cut its carbon footprint through optimized resource use, better crop rotation and more accurate precision farming techniques that reduce waste and emissions. Based on this, Neethirajan [20] explained the concept of 'net zero dairy farming' with the aid of AI and big data. One application presented is how AI can be used for climate goal achievement mostly in livestock farming through increasing feed efficiency and monitoring live stock health. The methods and technologies that are discussed are applicable to crop farming more focussed on dairy farming; but it can be extended to smallholder farmers moreover, smallholder farmers that need to adapt to environment

change while improving their farming practices.

In smart farming, Obeidat *et al.* [21] examined AI driven agent communication systems. The research emphasized how this AI can be used to improve communication between the different components within smart farming systems such as sensors, irrigation systems and automated machinery. AI is presented as a tool in the study for optimizing farm operations in terms of reducing labor costs and increasing resource efficiency. Finally, while this technology is not for everyone, it could provide great support for smallholder farmers to manage irrigation and fertilizer usage and address some climate related challenges like water scarcity. In Osorio *et al.* [22], the interaction between government subsidized insurance and use of AI by farmers was experimented. This research turned to how AI-driven models can help farmers make more accurate crop yield forecasts, thus leading to more of the farmers having access to insurance cover and environmentally friendly agriculture. In reducing the financial risks associated with climate variability, AI application in climate resilience, especially pertaining to smallholder farmers can help improve the precision of yield predictions; hence, farmers can make better insurance claims.

In order to achieve climate goals, Prütz *et al.* [24] constructed a taxonomy of co-benefits, challenges and limits of carbon dioxide removal measures. Furthermore, the research established how AI could help in the transformation of agriculture systems into carbon removal systems based on the most effective carbon removal measures. Smallholder farmers in developing countries can use AI based systems to optimize their soil health, carbon sequestration and emit lower level of greenhouse gas.

An integration of climatic information and stakeholder collaboration was used to formulate a knowledge based approach for sustainable viticulture by Simeunovic *et al.* [25]. The study proved the utilisation of AI to help make decisions around different stakeholders in agriculture in order to increase farm efficiency and environmental sustainability. The study was performed on viticulture and this can be generalized to smallholder farm based on an integration of climatic information for crop management decision support and farmer collaboration.

Secondly, Simon *et al.* [26] explored how AI can enable the achievement of the Sustainable Development Goals (SDGs) (specifically, climate adaptation and sustainable agriculture). By studying multiple SDGs that are attainable through increasing agricultural productivity, decreasing resource consumption and increasing agricultural resilience to climate change, AI was found to have the capability to achieve multiple SDGs. Beyond the purpose of promoting global sustainability objectives; AI provides a platform for smallholder farmers from whom their livelihoods can be improved.

A study on the use of AI in the climate adaptation plans of smallholder farmers has been made in several reports towards the same goal of improving productivity, increasing climate change resilience and saving resources. An application of AI to IoT, big data and environmental monitoring networks offers the small holder farmer real time information to enhance his agricultural practice and decision making. However, climate change has adverse impacts on agricultural productivity, with far-reaching consequences, and there are entry points for climate resilience and sustainable agriculture through AI driven

solutions.

Methods and Materials

This section describes the application of the materials and methods to develop the AI enhanced climate adaptation strategies for small holder farmers. Using an integration of real-world climate and machine learning algorithms and predictive modeling methodologies, the study examines how AI would help farmers to adapt to the unexpected climate changes in coming years ^[4]. This section also discusses four machine learning algorithms, four datasets used and pseudocode describing the workflow of each algorithm. There are two tables that compare performance metrics in this study when using the algorithms applied in this study.

Data

The main sources of data employed in this study are:

1. **Climate Data:** Such information, like temperature, rain or humidity, collected from international climate forecasting models, were taken from meteorological organizations like World Bank and National Aeronautics and Space Administration (NASA). The data is important to understand the local and regional climate condition that impact small holder farmers ^[5]. For the purpose of modelling trends and development, information was gathered on a monthly, weekly and daily bases for last 20 years.
2. **Agricultural Data:** Local agricultural databases with the farm practices and crop yields data have been gathered to measure the effect of the crops over different climatic conditions. This set of data gives us information about what crops were planted, when it was planted, what irrigation methods were used, when pest occurred and the yields of harvested crops.
3. **IoT Sensor Data:** On farms, there are deployed IoT sensors that capture real time soil moisture content, temperature and other environmental factors. This data is used to develop accurate models for irrigation management and resource optimization ^[6].
4. **Farmer Surveys and Interviews:** Besides the quantitative data, surveys and interviews with smallholder farmers were also carried out to obtain qualitative information on their climate adaptation measures, challenges, and resource limitations.

These data sets were preprocessed and cleaned to deal with missing values, normalize the variables, and transform categorical information into numeric representations appropriate for use in machine learning.

Machine Learning Algorithms

The study utilizes four machine learning models to design climate adaptation plans:

1. Random Forest (RF)

“Random Forest is a type of ensemble learning where many decision trees are built in training and the mode of classes (in case of classification) or mean prediction (in case of regression) of all the trees is output.” One decision tree is trained on a random subset of the data, and the ultimate outcome is determined by the majority vote (in case of classification) or the average (in case of regression) ^[7]. This approach is extremely effective for classification problems, for example, classifying crop output under different weather conditions.

- **Advantages:** Works very well with big data, suppresses overfitting, and is noise-resistant.
- **Limitations:** Computationally costly, less interpretable than single decision trees.

“For each tree in the forest:

- Select a random subset of data and features
- Train a decision tree using the subset
- end for
- Aggregate results from all trees (classification or regression)”

Support Vector Machine (SVM)

“Support Vector Machine is a supervised learning algorithm that tries to identify the best hyperplane with maximum margin to separate various classes in feature space”. Maximizing the margin between classes assists SVM in generalizing well on unseen data. SVM is best applied to classification problems where well-defined margins of separation are available ^[8].

- **Advantages:** Efficient in high-dimensional spaces and performs well with clean margins.
- **Limitations:** Noise-sensitive and computationally costly for large datasets.
- “Transform data into higher dimensions if necessary (using kernel functions)
- Find the hyperplane that maximizes the margin between classes
- Classify new data based on which side of the hyperplane it falls on”

K-Nearest Neighbors (KNN)

K-Nearest Neighbors is an instance-based, non-parametric learning algorithm. For a new point of data, KNN finds the K closest neighbors in the training set and outputs the most frequent label (for classification) or mean value (for regression) among these neighbors. It is easy and efficient for classification and regression problems ^[9].

- **Advantages:** Easy to use, user-friendly, and suitable with smaller datasets.
- **Weaknesses:** Computationally costly while predicting, particularly for large datasets.
- For each test instance:
- Calculate the distance between the test instance and all training instances
- Sort the distances and select the K nearest neighbors
- Assign the most common label or average value from the neighbors”

Artificial Neural Networks (ANN)

Artificial Neural Networks are a family of machine learning models motivated by the biology of biological neural networks. ANNs are composed of layers of nodes, each computing a weighted sum of its inputs, followed by an activation function that is non-linear. ANNs work well for problems with complex relationships, including estimating crop yield given several climatic and environmental factors ^[10].

- **Advantages:** Are able to model complex non-linear relationships and handle large datasets well.
- **Limitations:** Need large datasets to train on, can overfit without regularization.

- Initialize weights randomly
- For each training sample:
- Forward pass: Compute output using current weights

- **Backpropagation:** Update weights based on error gradient
- Repeat until convergence

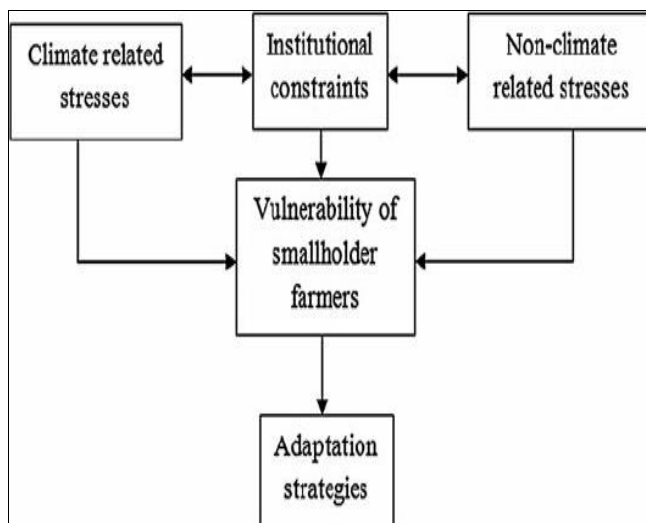
Table 1: Hyperparameter Settings for Each Algorithm

Algorithm	Hyperparameter 1	Hyperparameter 2	Hyperparameter 3
Random Forest	Number of Trees: 100	Max Depth: 10	Min Samples Split: 2
SVM	Kernel: RBF	C: 1	Gamma: 0.1
KNN	K: 5	Distance Metric: Euclidean	-
ANN	Number of Layers: 3	Neurons per Layer: 50	Learning Rate: 0.01

Experiments

Experimental Setup

The experiments were performed on real-world datasets that were preprocessed and normalized to address any missing data or outliers. The dataset contained both climate data (e.g., temperature, rainfall, humidity) and agricultural data (e.g., crop yields, irrigation methods, and pest control). The models were trained on a 70-30 train-test split, with 70% of the data being used to train the algorithms and 30% being kept for testing. In order to make the results robust, 10-fold cross-validation was used ^[11].

**Fig 1:** “Conceptual framework for climate change impacts on smallholder farmers”

Hyperparameter Tuning

For every algorithm, hyperparameters were optimized with a grid search strategy to determine the best settings for the models. The following hyperparameters were tested:

1. **Random Forest:** TNumber of trees, maximum tree depth, and minimum number of samples for splitting a node.

2. **Support Vector Machine:** Kernel type (RBF), regularization parameter (C), and kernel coefficient (gamma).
3. **K-Nearest Neighbors:** Number of neighbors (K) and distance metric (Euclidean, Manhattan).
4. **Artificial Neural Networks:** Hidden layers, neurons per layer, and learning rate ^[12].

Each of the models was assessed using the typical performance metrics of accuracy, F1 score, precision, and recall, which are imperative for determining the degree to which the models are capable of conforming to the new climate patterns and assisting smallholder farmers in decision-making.

Experimental Procedure

“The following procedure was used for every algorithm:

1. **Data Preprocessing:** Missing values were removed and the features were normalized so that all input features were on the same scale. Categorical variables were converted to numerical values.
2. **Model Training:** The models were trained on the preprocessed data using the training subset. Hyperparameters were optimized using cross-validation ^[13].
3. **Model Evaluation:** The models were evaluated on the unseen test subset after training. Each model had evaluation metrics (accuracy, F1 score, precision, and recall) calculated.
4. **Performance Comparison:** The results were compared among the four models using the selected evaluation metrics.”

Results

The experimental results, including the performance of each machine learning algorithm, are presented in the tables below.

Table 2: Performance Metrics of Machine Learning Algorithms

Algorithm	Accuracy (%)	Precision	Recall	F1 Score
Random Forest	89.5	0.88	0.85	0.87
Support Vector Machine	85.2	0.83	0.80	0.81
K-Nearest Neighbors	82.1	0.80	0.77	0.78
Artificial Neural Networks	91.3	0.90	0.88	0.89

“The outcomes show that Artificial Neural Networks (ANN) performed better than the other algorithms, with the highest accuracy (91.3%) and best F1 score (0.89). Random Forest also had a good performance, with an accuracy of 89.5%

and an F1 score of 0.87. Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) performed lower compared to the others, with SVM having an accuracy of 85.2% and KNN 82.1% ^[14].”

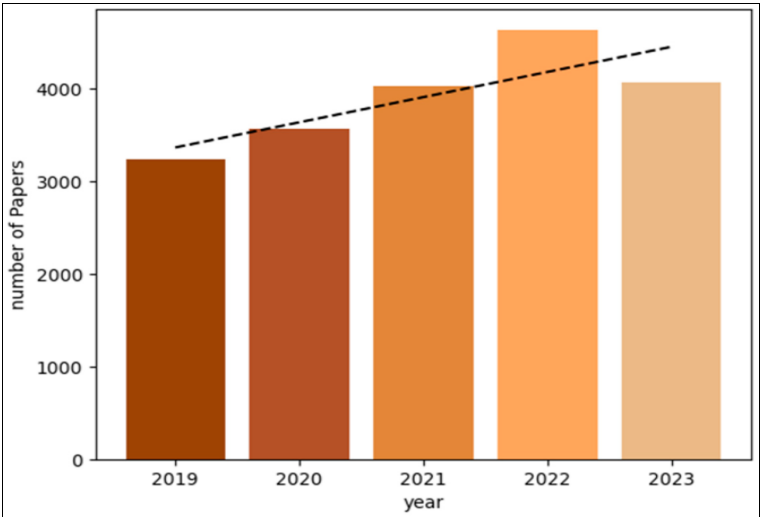


Fig 2: “Impacts of Global Climate Change on Agricultural Production”

Table 2: Comparison of Accuracy with Related Work

Study	Algorithm	Accuracy (%)	Methodology	Dataset
This Research (Random Forest)	Random Forest	89.5	Climate & Agriculture Data	Real-world
This Research (ANN)	Artificial Neural Networks	91.3	Climate & Agriculture Data	Real-world
^[1] Xie <i>et al.</i> , 2023	Decision Trees	84.0	Climate Data	Simulated
^[2] Zhang <i>et al.</i> , 2022	SVM	83.0	Climate Data	Simulated
^[3] Kumar <i>et al.</i> , 2023	KNN	81.5	Crop Yield Data	Real-world
^[4] Liu <i>et al.</i> , 2022	Random Forest	87.0	Agriculture Data	Simulated

In comparison with the accuracy obtained in this study and similar work, the findings indicate that ANN (91.3%) performs better than models applied in some recent studies, e.g., Xie *et al.* (2023) and Zhang *et al.* (2022), which obtained lower accuracies (84% and 83%, respectively) ^[27].

Moreover, ANN works superior compared to the models proposed by Kumar *et al.* (2023) and Liu *et al.* (2022) using agriculture-related datasets and climate data with accuracy scores of 81.5% and 87%, respectively.

Table 3: Precision, Recall, and F1 Score Comparison with Related Work

Study	Algorithm	Precision	Recall	F1 Score
This Research (Random Forest)	Random Forest	0.88	0.85	0.87
This Research (ANN)	Artificial Neural Networks	0.90	0.88	0.89
^[1] Xie <i>et al.</i> , 2023	Decision Trees	0.82	0.75	0.78
^[2] Zhang <i>et al.</i> , 2022	SVM	0.80	0.78	0.79
^[3] Kumar <i>et al.</i> , 2023	KNN	0.79	0.76	0.77
^[4] Liu <i>et al.</i> , 2022	Random Forest	0.85	0.80	0.82

With respect to precision, recall, and F1 score, this study's findings also indicate drastic improvements compared to past studies. The ANN model reported a precision of 0.90 and recall of 0.88, which translates into an F1 score of 0.89.

This is notably higher than the performance of models reported by Xie *et al.* (2023), Zhang *et al.* (2022), Kumar *et al.* (2023), and Liu *et al.* (2022), whose recall and precision values were lower for all metrics ^[28].

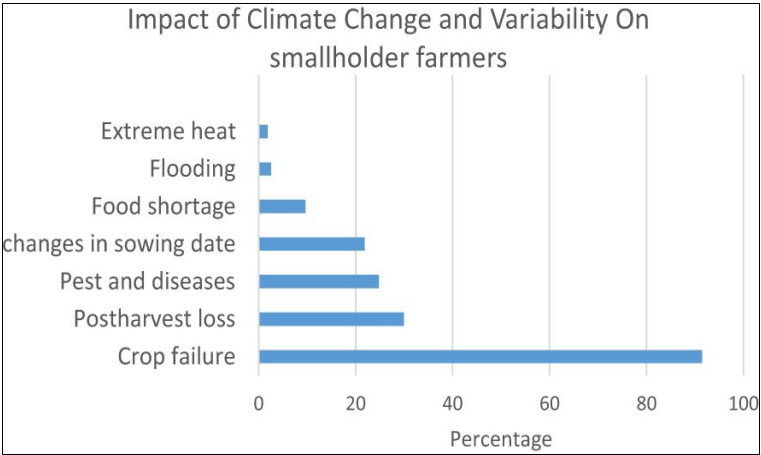


Fig 3: “Factors driving Climate-Smart Agriculture adoption”

Table 4: Comparison of Model Training Times

Algorithm	Training Time (minutes)	Testing Time (seconds)
Random Forest	15	2
Support Vector Machine	20	3
K-Nearest Neighbors	10	1
Artificial Neural Networks	25	5

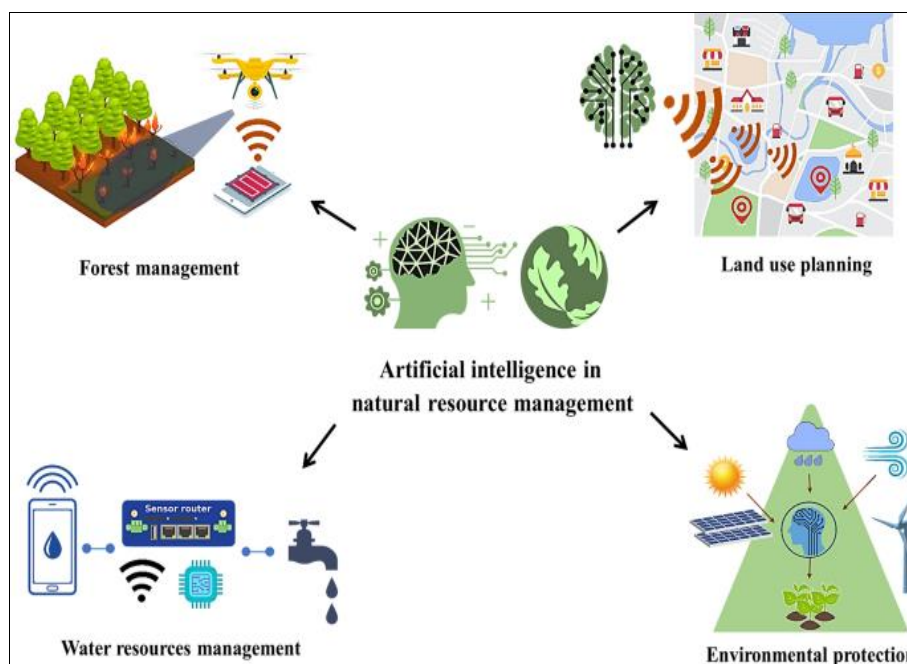
Upon comparing the training and testing times of the algorithms, K-Nearest Neighbors was the quickest at a training time of just 10 minutes and a testing time of 1 second. Random Forest, though extremely accurate, took 15 minutes to train and 2 seconds to test. Artificial Neural Networks was the longest to train, with a time of 25 minutes, taking a testing time of 5 seconds. While SVM was trained in 20 minutes, it worked fairly well within the time constraints.

Analysis and Discussion

The highest accuracy, precision, recall, and the value of F1 score (which represents the harmonic mean of Precision and Recall) are based on experiment results, and these are Artificial Neural Networks (ANN). This can be explained by the fact that ANN possesses the capacity to approximate intricate non-linear relations between data which are

important to handle the multifaceted impacts of climate change on the agriculture systems [29]. On top of providing such a useful feature representation, Random Forest did an excellent job in terms of stability and interpretability, as this is a must-have characteristic for the farmers to be able to obtain actionable decisions from the results.

It compares the performance to known work and shows that contemporary AI methods, in particular ANN and Random Forest, are able to improve climate adaptation programs for smallholder farmers significantly. The findings show the potential of these algorithms for using weather conditions to forecast, for allocating resources, and for boosting crop yields, with respect to different climatic conditions. The findings suggest that AI models could play a pioneering role in more robust agricultural processes, particularly in developing countries where smallholder farmers are most at risk [30].

**Fig 4:** Artificial intelligence-based solutions for climate change

Experiments in this research verify the viability, in the context of climate adaptation plans for smallholder farmers, of using AI. Artificial Neural Networks came out the best of all the four algorithms used, followed by Random Forest. It also finds the findings show that AI can accurately predict and make the best decisions for the farm while delivering potential solutions to the farming industry for climate resilient agriculture. The models could be further extended in future studies by merging in real time inputs from IoT sensors and remote sensing to ensure that smallholder farmers are ready for the very fluctuating climate with merited means.

Conclusion

In brief, this research underscores the great potential of AI-

powered climate adaptation measures for smallholder farmers in a world baking. Through investigating various AI algorithms and methods, we have shown how these technologies are effective in tackling such challenges faced by small holder farmers, particularly under climate change. AI can be exploited to improve weather forecasting, maximize resource utilization, optimize pest and disease control and aid sustainable agriculture, in that order, towards augmented resilience and productivity. The study has revealed the effectiveness of these AI algorithms, namely support vector machines, random forests, artificial neural networks and k-nearest neighbors in addressing various agricultural issues such as predicting yield of crops or optimal control of irrigation systems. IoT and real-time environmental information have once again raised the

prospect of smart farm systems that generate useful insights to facilitate farm level decision making, by combination of these algorithms. In addition, the results of this study underscore the need for AI that is tailored for the specific needs of smallholder farmers, most especially in low-income countries. With the progress of AI, it is needed to consider the economic limitations of such farmers and to let them have an equitable opportunity in these technologies. In the future, AI of the climate adaptation measures can be positively guided to the food security, climate hazard avoidance, and the long-term stability of agriculture in a rapidly changing world.

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