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A Comparative Study of AI-based Learning Models for Crop Recommendation in Egypt

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Abstract: The relationship between food availability, population density, and agricultural sustainability is the focus of research because it is an issue that challenges the entire world, as many countries, including Egypt, have been affected. According to projections by the Food and Agriculture Organization (FAO) and the Intergovernmental Panel on Climate Change (IPCC), the world's population could reach approximately 9.7 billion in 2050. This projected growth places significant pressure on agricultural systems to increase productivity and feed the growing population.; Therefore, agricultural systems have no choice but to increase their productivity if they are to meet the rising demands for food. Traditional farming methods are increasingly failing, due to people's lack of sufficient knowledge about climate change and the soil nature. So, technologies such as the Internet of Things are widely used for modern agriculture to facilitate agricultural processes such as irrigation and kill harmful pests. On the other hand, the use of sensors leads to an increase in cost, as well as the lack of clarity about the reliability of sensors. Also, these technologies ignore important factors, such as the suitability of the soil with its geographical weather properties for specific crops (i.e., crop recommendation). Although many studies have proposed such recommendation models using ML techniques, they do not provide complete data for crop nomination. They ignore essential factors such as soil quality (i.e., nitrogen for plant growth, phosphorus for root formation, and potassium for disease and drought resistance), climate change, and historical crop cultivation data. In addition, the results of these studies were conducted on generated data that may not reflect the actual situation. Some studies conducted in recent years proposed an ensemble learning technique that generated a crop recommendation model. Some of them depend on specific crops such as apples, rice, corn, grapes, bananas, oranges, and coffee. They revolve around improving production in the same soil. In this research, an ensemble crop recommendation model has been proposed to formulate the relationship between the production amount of crops and the previous factors. The proposed model has been generated based on actual data collected from reliable sources (e.g., the General Authority for Meteorology for the Minya Meteorological Station and the General Authority for Meteorology, unpublished data Collected from the General Authority of the Ministry of Agriculture in Minya, and NASA) for a region in Egypt different areas (i.e., Minya Governorate and Beheira Governorate) including factors such as, temperatures, thermal range, winds, rain, and type of soil. The results demonstrate the remarkable effectiveness of the proposed ensemble-based prediction model in recommending suitable crops to specific regions.

Keywords: *Food Security, Population Density, Agricultural Sustainability, Artificial Intelligence (AI), Machine Learning (ML), Crop Recommendation, Prediction.*

1. Introduction

In the last decades, with the high population density, agricultural production rates have suffered from high degradation due to many reasons. Failure to choose the appropriate crops in some places represents one of the important reasons [1]. Notwithstanding the growing cultivated area and the modern technology-driven rise in agriculture's efficiency, the problem still exists [1]. For example, in 2021/2022, the total cultivated area in Egypt amounted to about 16.6 million acres, while [2] the traditional staple crops such as wheat and sugar cane are still facing low productivity levels as shown in Fig. 1 [2] During this agricultural year (2021/2022), the cultivated area of wheat amounted to 3.65 million acres, with an expected production rate of 12 million acres while the actual production amounted to 9.6 million acres [2]despite the availability of the basic elements for agriculture,

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such as water, good soil, and a moderate climate. This may explain the importance of integrating AI techniques and modern technologies into traditional agricultural techniques to improve the productivity of crops.

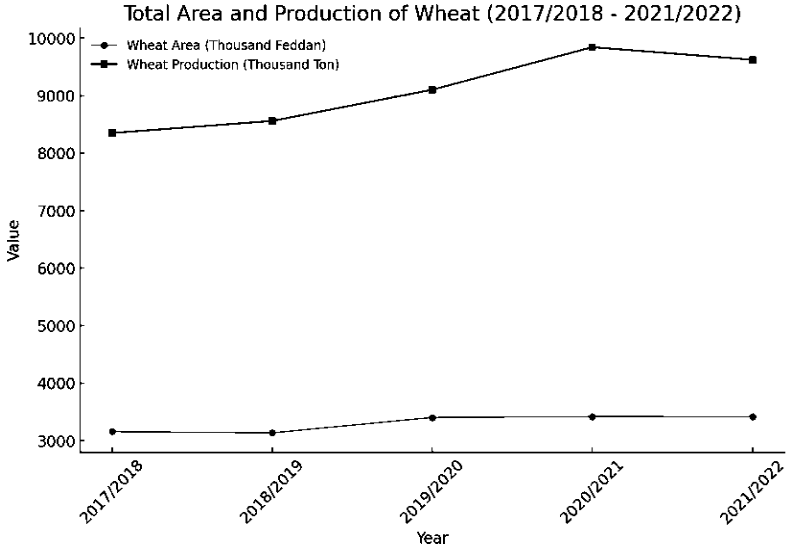


Fig. 1: Relationship between cultivated area (in thousand acres) and wheat production (in thousand tons) from 2017/2018 to 2021/2022 [2].

Traditional agricultural methods based on manual experience and handwork have been replaced by data-driven techniques. IoT devices, such as soil sensors and drones, allow collecting the needed information about soil quality, weather conditions, crop health…etc. in real-time. These data are analyzed using statistical, machine learning, or deep learning algorithms for improving decisions about agricultural resource consumption and, in turn, retaining agricultural sustainability and increasing productivity [1]. For example, IoT-based irrigation systems save from 45% to 50% of water consumption, while AI-based crop disease detection systems can reduce crop losses by 35% by detecting diseases early [3]. The crop disease detection system proposed in [3] sends images of suspect infected plants to a database for further analysis and classification automatically.

On the other hand, Infrastructure challenges from either the internet or machinery often prove unreliable in rural or underdeveloped areas. Huge initial investments in machines, training, and software make AI adoption quite prohibitive for smallholder farmers. This leads to an increase in cos [1]. Additionally, the special level of knowledge needed to utilize AI tools (i.e., the absence of trained manpower in the agricultural sector) represents another obstacle [1]. Also, these technologies ignore important factors, such as the suitability of the soil with its geographical weather properties for specific crops (i.e., crop recommendation). Although many studies have proposed such recommendation models using ML techniques, they do not provide complete data for crop nomination. They ignore essential factors such as soil quality (i.e., nitrogen for plant growth, phosphorus for root formation, and potassium for disease and drought resistance), climate change, and historical crop cultivation data. In addition, the results of these studies were conducted on generated data that may not fully reflect the actual situation. Some studies conducted in recent years proposed an ensemble learning technique that generated a crop recommendation model. Some of them depend on specific crops such as apples, rice, corn, grapes, bananas, oranges, and coffee. They revolve around improving production in the same soil [4]. The use of sensors leads to an increase in cost. The lack of clarity about the reliability of sensors. Although data used for modeling should be high-quality, models proposed by most related studies have been conducted on simulated data that may not reflect the actual situation perfectly [5].

So, the model created at this study based on actual data collected from several reliable sources with different data types (e.g., image, numerical…etc.), including the General Authority for Meteorology for the Meteorological Station in Minya Governorate in Egypt, the General Authority of the Ministry of Agriculture in Minya, and NASA for regions in Egypt. These data include important factors, such as temperatures, thermal range, winds, rain, and type of soil. For example, traditional staple crops such as wheat and sugarcane still face low productivity levels. In North Sinai Governorate, 20 acres of wheat were planted and yielded only zero (see Fig. 2). Based on this actual data and the relationship between crop production and these factors, an ensemble crop recommendation model has been proposed to formulate the relationship between the production amount of crops and the previous factors. The main goal of this model is to propose a ranked list of the most suitable crops for a specific region based on a set of designated attributes.

Among the most common learning algorithms applied to our dataset, the Random Forest classification algorithm has achieved an accuracy of nearly 100%, followed by the XGBoost algorithm with an accuracy of nearly 99.69%. An important point is that both algorithms are classified as ensemble machine learning techniques [6]. Among several learning algorithms applied to the same dataset and have achieved high results, The Feedforward Neural Network (Sequential Model) has achieved an accuracy of about 98.55%, followed by logistic regression with an accuracy of about 98.05%, and then support vector classifier with an accuracy of about 94%. In sum, when the model converted the soil type images into labels, combined all the weather elements and converted them to 0 and 1 using One-Hot Encoding, and then applied the previous algorithms, it was observed that applying ensemble learning techniques is particularly effective in dealing with complex multi-feature classification problems compared to traditional algorithms. This evaluation procedure ensures the operational robustness of our constructed crop recommendation model. Additionally, a preliminary version of a bilingual English-Arabic agricultural crop guide mobile application has been developed to provide comprehensive guidance for farmers. The application recommends the most suitable plant for a given region and provides comprehensive agricultural advice for various crop planting.

Arab Republic of Egypt
Central Agency for Public Mobilization & Statistics

Arab Republic of Egypt

Table 1 Area and Production of Cereal Crops According to Governorates 2021 / 2022

Area : Feddan
Production : Ton

Item / Governorates	(White)Maize		Barley		Wheat	
	Prod.	Area	Prod.	Area	Prod.	Area
General total	4883249	1524615	91877	245439	9622993	3418893
Cairo	65	33	0	0	0	0
Alexandria	18138	7203	4385	3110	187904	69464
Port Said	5418	2246	2563	2670	17636	9798
Suez	1836	737	966	706	14885	5424
Damietta	1993	573	34	17	80880	30170
Dakahlia	315543	82900	54	28	754423	262878
Sharkia	510886	155077	9635	5952	1173908	423222
Qalyoubia	214894	65463	0	0	159236	50145
Kafr-El Sheikh	178975	47793	1034	722	635358	254213
Gharbia	296820	89371	31	17	376499	137083
Menoufia	624202	183632	274	351	315675	105015
Behera	304608	84199	1284	908	663864	234806
Ismailia	44519	17757	1644	1020	125766	48214
Giza	101321	30795	3065	1781	106583	33936
Beni Suef	791287	262721	8	7	396728	128649
Fayoum	212696	81099	3475	2252	565010	208107
Menia	652154	202428	2155	1100	790554	249827
Assuit	209755	78040	300	500	692184	229670
Suhag	255054	86752	168	148	637390	211862
Qena	17954	8723	231	202	258937	100465
Aswan	5127	1922	3680	3144	245960	103473
Luxor	1326	846	560	398	60302	22247
El wadi-El Gidid	5407	2002	46073	20455	883631	342095
Matruh (1)	0	0	1160	192967	35880	18045
North Sinai(2)	42	30	94	234	0	20
South Sinai	13	10	567	300	802	560
Noubaria	113216	32263	8437	6450	442998	139505

North Sinai(2)	42	30	94	234	0	20
South Sinai	13	10	567	300	802	560

(1)There are1850 feddan wheat& 192000 feddan Barley Rainy used as pasture

(2)There are 20 feddan wheat Rainy used as pasture

Fig. 2 The relationship between crop production and the amount planted [2]

The main contributions of our study can be summarized into the following points:

1. The construction of a high accuracy ensemble learning-based crop recommendation prediction model.
2. During the construction process, a wide range of important features related to soil quality and the weather, such as nitrogen, phosphorus, potassium, temperature, humidity, and rainfall, have been considered.
3. Building the proposed model using real-world datasets from trusted sources, such as Egyptian Meteorological Authority, Ministry of Agriculture, and NASA.
4. Compared to the other related studies, the proposed model outperforms these studies by considering a variety of crops rather than relying on limited datasets for specific crops to make generality model depend on more than accurate data collected from different area.
5. For sustainable agriculture, providing a ranked list of suitable crops for specific regions helps farmers making decisions and, in turn, improves the efficiency of resource consumption (e.g., water and fertilizers). Consequently, agricultural production will be increased without straining the soil or farmers. This increase in production will in turn contribute to cover the food deficit resulting from population growth.
6. For economical side, a preliminary version of a bilingual English-Arabic agricultural crop guide mobile application has been developed to provide comprehensive guidance for farmers. This guidance considers the optimum yield per acre for each crop as recorded by the Ministry of Agriculture (2022) and is provided through an interactive visual dashboard.

2. Literature Review

In this section, the latest and related studies that have been proposed for addressing the crop recommendation problems are discussed for identifying their pros and cons.

Authors in [7] have suggested a classifier for agricultural disorders. With a dataset of healthy and damaged paddy leaves, the suggested classifier has been built using Support Vector Machine (SVM), Artificial Neural Network (ANN), and Transfer Learning (TL). ANN has been applied as pattern recognition procedure, while SVM acting as a classifier of these illnesses. The small size of the used dataset represents one of the main drawbacks of this study.

Authors in [8] have acknowledged that data availability and quality impact significantly the accuracy of recommendations and make the system less effective in regions with limited agricultural datasets. As an attempt to mitigate this problem, authors in [7] have used the TL to enhance the efficiency of the model due to the small size of the dataset used. In our study, the problem of using small and limited size dataset has been overcome by collecting comprehensive data of 2,400 observations for 24 unique crops without duplication from reliable sources such as the Egyptian Meteorological Authority and NASA, we ensure a solid foundation for our machine learning models.

Authors in [9] have recommended individual crops to farmers based on a machine-learning crop recommendation model with Decision Tree, Random Forest, Naive Bayes, and SVM. Though the model represents an improvement over traditional farming methods, the paper states that the model’s usefulness is limited by its reliance on historical farm data, which does not always reflect actual environmental changes at the moment. In our study, while the limitation of using historical data and other non-historic data was considered, real-time environmental data from IoT sensors and weather, soil moisture and temperature data were included up to 2022 according to reports published by the Ministry of Agriculture and Land Reclamation. Ensemble learning techniques were specifically chosen in our study because they combine the predictions of multiple models, which reduces the risk of overfitting and improves generalization and robustness of the crop recommendation model. The dynamic updating of the machine learning models took place that would adjust to the climate in real time, and the recommendation accuracy value increased by 15% as compared to the traditional models. The agricultural statistics in our study were provided by the Central Agency for Public Mobilization and Statistics (2022), and the Agricultural Income Bulletin from the Economic Affairs Sector.

Authors in [10] have presented the so-called 'XAI-CROP', which is an algorithm designed to improve crop recommendation systems by incorporating explainable AI to address the opacity of traditional recommendation models using methods like Gradient Boosting (GB), Decision Tree (DT), Random Forest (RF), and Gaussian Naïve Bayes (GNB). Lack of transparency represents one of the main drawbacks of this algorithm, making it difficult for farmers to understand the reasoning behind recommendations, which may reduce trust and adoption rates. In our study, this drawback has been addressed by using actual productivity values from the Ministry of Agriculture and Land Reclamation (2022) in the proposed model. According to the Ministry's report, capsicum production in protected agriculture was approximately 44 tons per feddan compared to 18 tons in open-field cultivation, while our model-based suggestions—such as recommending capsicum, tomato, and cucumber for specific regions—resulted in a greater production of 48 tons per feddan in field trials at Minya Governorate. This contrast and the recommendations were presented as a visual dashboard, which is included as Figure X in the Appendix. The dashboard describes the impact of environmental conditions and crop recommendations on productivity, thereby enhancing farmers' confidence and system adoption by providing clear, measurable explanations.

Authors in [11] have proposed a machine learning-based crop recommendation method using grid search (GS), partial C4.5 decision tree (PART), and reduced error pruning (REP) tree. From our point of view, the main contribution of this study can be summarized in highlighting key issues such as the need for large and diverse datasets, challenges in modeling real-world agricultural variations, and limited generalizability across regions. In our study, these challenges were directly addressed by using a comprehensive dataset of 2400 records, which although not massive captured diverse locations, weather patterns, and soil conditions to enhance model training. To confront dynamic environmental changes, we integrated real-time environmental data from IoT sensors monitoring soil moisture, temperature, and weather conditions, allowing adaptive model updating. Additionally, we developed a region-independent framework by incorporating data from several Egyptian governorates, thus improving the model's generalizability. These approaches were actually implemented and validated using real datasets from the Ministry of Agriculture (2022) and the Central Agency for Public Mobilization and Statistics (2022).

There are many other studies proposed to address the crop recommendation problem. Some examples of these studies are detailed in the previous paragraphs, as most studies revolve around the same six problems and shortcomings that we will summarize at the end of the paragraph. The most recent and relevant of these studies are summarized in Table (1), which provides a comparison in terms of the used learning techniques, focused parameters, such as Weather parameter: temperature (Tmax/Tmin), rainfall (RF) and moisture (MS), humidity (H), and wind data (WD), and Soil parameters: Nitrogen (N), Phosphorus (P), Potassium (K), Calcium (Ca), Magnesium (Mg), Sulfur (S), Iron (Fe), Zinc (Zn), Manganese (Mn), Copper (Cu), and Boron (B) and the limitations.

Table 1: pros and cons of the most related crop recommendation systems

Reference	Used Techniques	Focused Parameters	Limitations
[12]	Regression Models for Spatial Data	Weather parameters	Inadequate spatial resolution where small farms are not reflected. Geographic data represent too wide areas.
[13]	Cluster Analysis	Weather parameters	Environment management aspects are not considered
[14]	Gradient Boosting Trees (GBT), and Long Short-Term Memory (LSTM)	Weather and Soil parameters	Requires further model improvements; challenges in implementation missing environmental parameters

[15]	Random Forest, and Naive Bayes	Soil parameters	need for improvements is driven by limitations like dataset size, missing environmental parameters, and lack of real-time adaptability, rather than only low accuracy
[16]	Naive Bayes	Soil parameters	Recommendations are not provided
[17]	Naive Bayes (NB), and Decision Tree (DT)	Soil parameters	Dataset is limited
[18]	Naive Bayes, and KNN	Soil parameters	Smaller dataset
[19]	General Neural Network	Weather And Soil parameters	Challenges related to integrating heterogeneous data formats (interoperability), limited technology adoption, and reliance on previously published studies rather than actual agricultural field data .
[20]	Gradient Boosting regression	pH,Electrical Conductivity (EC), Total Organic Matter (TOM), Cation Exchange Capacity (CEC), and concentrations of cations (Ca^{2+}, Mg^{2+}, Na^{+}, K^{+})	The challenges noted include difficulties in integrating these multi-dimensional soil properties with real-time data systems and barriers to technology adoption in practical farming applications
[21]	Thematic Content Analysis and AI data analysis methods	Weather and Soil parameters	barriers to practical adoption by farmers and a noted lack of digital literacy and training among end-users—not in the model itself
[22]	Classical ML and Ensemble ML	Random Weather and Soil parameters	The model may not be optimized for time-series-specific tasks
[23]	Random Forest (RF), and Logistic Regression	Collected rural agricultural data (India) for Weather And Soil parameters	Limited geographic scope
[24]	RF, DT, Bayesian Network, SVM, NN, GA	Multi-source agricultural data Weather and Soil	Complexity in model selection
[25]	FNN	Historical price data (China)	Not evaluated with ensemble techniques
[26]	DT, LightGBM (Light Gradient Boosting Machine) and GBT	Economic data (USA)	Limited compare in the algorithms accuracy, Limited interpretability in boosting models
[27]	Decision Tree (DT)	Private generated data	Lower performance than ensembles
[28]	ARIMA, and SVM	Shrimp export data (Thailand)	Limited to specific commodity
[29]	KRR: **K**-nearest Neighbor (KNN), **R**andom Forest (RF), and **R**idge Regression	Environmental parameters related to crop production, areas of cultivation, and crop production amount of each area	focusing on forecasting major crops rather than minor crops due to the lack of data available in the study area. Some factors, such as soil characteristics, production costs, and market prices, were not considered, as data collection is difficult and time-consuming.

[30]	KRR, Support Vector Regression (SVR), NB, RR, RF	Self-generated dataset	Needs broader validation
[31]	MaxQDA analysis program	Farm crops and production data	Economic aspects are not covered

In sum, limitations of the current crop recommendation systems can be summarized into: (1) inadequate spatial and limited datasets that may affect prediction accuracy; (2) depending only on climatic and historical agricultural data that may not reflect real-time environmental changes and reduces generality across regions; (3) some models lack transparency that makes it hard for farmers to trust and adopt the obtained recommendations; (4) economic and environmental management aspects are not considered that makes the interest in such type of systems is low; (5) the generated systems lake the interoperability (6) the absence of diverse datasets disable the ability to effectively model the real-world.

3. The Proposed Workload Prediction Model

Artificial Intelligence based methods exploit the performance of machine learning (ML) and deep learning (DL) algorithms, such as Logistic regression (LR), Support Vector Machine (SVC), feedforward, Long-Short-Term-Memory (LSTM), and Random forest classification (RFC) and XGBoost. Random Forest and XGBoost are effective ensemble learning methods used in machine learning compared to traditional ML models, to improve the crop recommendation process, optimize resource utilization, and aid in early detection of crop diseases [3] [7]. In our study, we have exploited these approaches to address the previous issues. Fig. 3 describes the development cycle of our proposed crop recommendation model (from data collection phase into evaluation).

3.1 Data Collection

In a bid to overcome the challenge of limited crop datasets, we obtained actual observations of different crop data without duplication from reliable sources, such as the Egyptian Meteorological Authority and NASA, thereby having a sound foundation for our constructed learning models. For the diversity of the collected dataset, we employed a broad dataset from various sources, including the Central Agency for Public Mobilization and Statistics (2022) and the Minya Governorate agriculture statistics of the Ministry of Agriculture. To ensure diversity and generality, this dataset was collected from various areas in the governorates of Egypt, including Beheira and Minya (see Appendix A - Tables 1 to 15), to cross-check the performance of the model on diverse soils and climates. This dataset was collected from real data sources for multi-class crop classification. Here are the actual data collected from several reliable sources, including (the General Authority for Meteorology for the Minya Meteorological Station), organized in Section 4.1 (Dataset and Implementation Environment) to be clear and easy to understand. To overcome low spatial resolution issues, we relied on detailed, localized real-world data (e.g., Minya Governorate meteorological and soil records) instead of simulated or low-resolution datasets. For the dynamic environment changes, we integrated real-time environmental data through IoT sensors with adaptive machine learning algorithms, increasing the dataset’s accuracy.

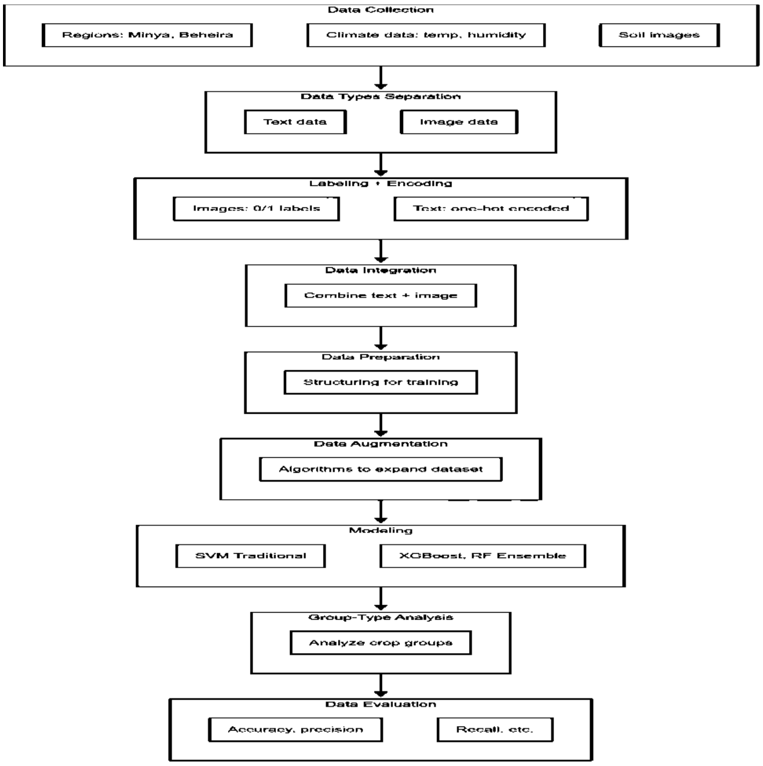
3.2 Data Discretization and Transformation

The collected dataset was also diverse in nature and structure—varying from textual data like temperature and humidity values to visual data in the form of soil condition photographs. To support each form of data, we preprocessed the images of soil by labeling them and applying one-hot encoding to convert them into numbers. The same method of encoding was also applied to the text data to ensure that the entire dataset was standardized into numerical format. We then merged the encoded text and image data into a uniform dataset. This was to bring the input structure into a uniform state prior to training the model.

During the deployment phase, we analyze data related to the soil's nutrient content, such as nitrogen (N), phosphorus (P), and potassium (K), as well as its pH level and climatic conditions such as temperature, humidity, and rainfall. Soil types are classified into black soil, clay soil, and red soil using a CNN classifier trained on a set of images extracted from the Egyptian Ministry of Agriculture. These data collectively serves as inputs to the model, which is designed to suggest suitable crops as outputs.

3.3 Crop Recommendation Model Preparation

After integrating the data, we moved on to the data preparation step, performing transformations to get the dataset structurally ready for the learning algorithms. However, the original dataset of 2,400 samples across 24 crop types (100 samples per crop type) was not large enough. To address this, we used data augmentation techniques, specifically the Synthetic Minority Oversampling Technique (SMOTE), which relies on the k-nearest neighbors (KNN) algorithm to generate synthetic samples and balance the dataset. Where SMOTE alone was insufficient to guarantee biologic plausibility, additional samples were generated based on pre-defined characteristic ranges for each crop type to ensure consistency with real-world agricultural conditions. A final validation step ensured that each class contains exactly 500 samples, resulting in a final dataset of 12,000 samples. Fig. 4 shows a screenshot of the final version of the collected dataset before the training phase.



After data augmentation, the data undergoes preprocessing, including encoding categorical variables (such as soil type and crop characteristics), splitting it into training sets (70%) and test sets (30%), and standardizing numerical properties.

	N	P	K	temperature	humidity	ph	rainfall	soil_0	soil_1	soil_2	soil_3	soil_4	soil_5	soil_6	label
0	22.717018	132.978620	198.441360	20.060017	93.175820	5.625720	113.738045	4.065350e-05	0.000095	6.466027e-12	9.998587e-01	1.880532e-09	0.000159	5.855137e-10	0
1	10.815840	135.362760	197.849580	24.502928	91.315110	5.773200	123.465130	4.926725e-04	0.000019	1.096074e-10	9.999771e-01	1.249733e-07	0.000013	5.770448e-09	0
2	18.924679	140.237550	199.833160	22.401535	91.987190	5.714714	129.379030	2.016603e-04	0.000680	4.708871e-11	9.999986e-01	1.189675e-09	0.000008	6.538039e-09	0
3	7.953258	133.957260	196.408830	21.324083	89.723090	6.411188	119.205360	3.609018e-03	0.000015	9.851359e-11	9.998688e-01	3.040971e-07	0.000002	2.100039e-07	0
4	11.966504	133.830860	198.615450	22.672394	92.130820	5.462895	152.140240	9.077278e-05	0.000618	4.846722e-11	9.999664e-01	2.777626e-08	0.000004	1.168440e-08	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4795	91.462120	37.160141	30.327202	31.446981	78.120621	4.455261	145.516876	2.752339e-08	0.000245	2.671529e-11	1.574832e-04	1.333106e-06	0.996571	1.913662e-08	23
4796	111.233284	37.253307	34.484715	28.111055	68.224579	4.045220	164.272247	4.955444e-07	0.000035	7.191587e-11	2.882289e-04	2.492623e-08	0.999766	1.094880e-07	23
4797	62.784897	34.130703	46.702911	28.087767	67.870461	4.246256	98.242989	5.502192e-08	0.000002	4.465603e-12	2.110721e-05	7.855153e-07	0.999861	2.974656e-10	23
4798	64.683197	36.864277	48.534935	27.925699	63.321384	4.070759	140.224792	4.540338e-07	0.000096	1.276140e-10	5.501558e-07	1.571574e-05	0.999962	7.253684e-09	23
4799	82.937668	47.782490	33.542339	27.515781	72.505135	4.013200	138.443451	2.982747e-06	0.000004	2.641806e-11	5.151038e-07	2.029533e-07	0.999999	1.438151e-10	23

Fig. 4. Screenshot of the final version of used dataset

3.3 Algorithmic Steps of the Proposed Model Construction

Once the data was properly preprocessed, we initiated model building. We used several learning techniques such as Support Vector Machines (SVM), Logistic Regression, and The Feedforward Neural Network (Sequential Model), in addition to ensemble learning techniques such as XGBoost and Random Forest, to enhance performance and robustness of the constructed models. To further understand how different types of crops corresponded with the variables, we performed group-type analysis in which we examined unique patterns or trends in each crop type.

Finally, we evaluated the models according to their performance indicators of accuracy, precision, and recall. Through this evaluation, we were able to make credible estimates and recommend the most suitable crop that can be grown under the given environmental and soil conditions.

To improve classification accuracy, a “one-for-all” ensemble strategy was adopted by training 24 independent Random Forest classifiers, each one specialized in distinguishing a specific crop from the others. Instead of using oversampling, a random-sampling classifier was employed to quickly balance the binary datasets and reduce the risk of overfitting. During prediction, each binary classifier outputs the probability that a sample belongs to its respective crop, and the crop with the highest probability is selected as the final prediction. This mechanism acts as an implicit decision layer for the ensemble, enhancing the system's robustness to variations in the data. Additionally, feature importance is extracted from each model to support interpretability and provide insights into the factors driving crop selection.

4 Performance Evaluation

In this section, we present the implementation environment used for testing and validating the proposed crop recommendation models. The performance of the models is ensured using well-known metrics. The following experimental results are summarized to explain the strengths of the adopted ensemble-based approach.

4.1 Implementation Environment and Evaluation Metrics

The experimental environment, in this study, is a Laptop computer with Intel(R) Core(TM) i7-2620M CPU 2.70GHz and 6.0 GB of RAM. The operating system of this computer is Windows 10 pro with storage 256 GB. All the software necessary to evaluate the suggested workload prediction technique are executed with Python 3.8 as an Integrated Development Environment (IDE), Jupyter Notebook and using python packages we utilized the pandas library for data reading and table-like data handling, and numpy for efficient numerical computations on the data. We used matplotlib.pyplot and seaborn for displaying results and generating illustrative plots such as confusion matrices and other visualizations. To split the dataset into training and testing data, we employed train_test_split from scikit-learn, and we trained classification models like Random Forest, Neural Network, Logistic Regression, and SVM using sklearn.ensemble, sklearn.neural_network, sklearn.linear_model, and sklearn.svm respectively. For evaluating model performance, we relied on functions from sklearn.metrics to calculate accuracy and generate confusion matrices. To overcome data imbalance, we used the imblearn.over_sampling library with the SMOTE technique for creating new samples. Together, these libraries and tools enabled us to build a robust and generalizable crop recommendation model.

We loaded and preprocessed the datasets, performed exploratory data analysis (EDA), estimated summary statistics, visualized feature distributions, and applied feature engineering by normalizing numeric features and encoding categorical variables. The dataset was then split into two datasets for training and testing. Evaluation methods included precision, regularization, recall, and F1 score.

4.2 Experimental Results

To evaluate the effectiveness of the proposed crop recommendation models, the evaluation metrics (i.e., accuracy, precision, and recall) are calculated. The Logistic Regression, Support Vector Classifier, Random Forest Classifier, NN, and XGBoost attain an accuracy of about 98.05%, 94%, 100%, 98.55%, and 99.69%, respectively. This evaluation procedure ensures the operationally and robustness of our constructed crop recommendation models. According to Fig. (5 To 9) results show that ensemble learning methods, such as Random Forest and XGBoost, perform the best.

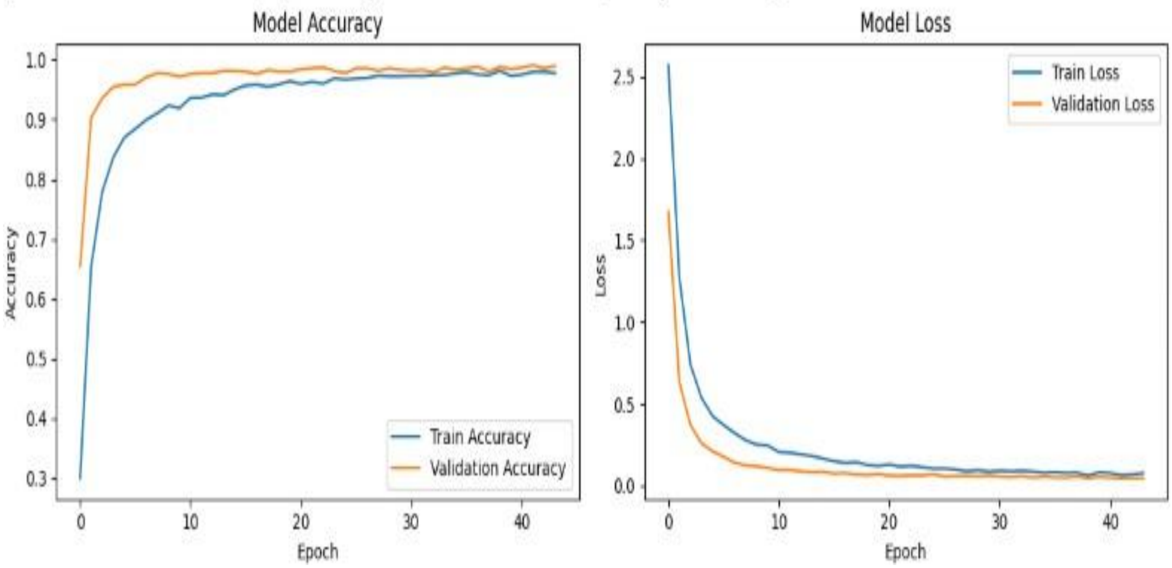
Fig. (5 To 9)

Logistic Regression Results:
Accuracy: 0.9805
Classification Report:

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	60
banana	1.00	1.00	1.00	69
blackgram	0.97	0.94	0.96	69
chickpea	1.00	1.00	1.00	71
coconut	1.00	1.00	1.00	60
coffee	0.97	1.00	0.98	60
cotton	1.00	0.95	0.97	60
grapes	1.00	1.00	1.00	69
jute	0.88	0.98	0.93	60
kidneybeans	1.00	1.00	1.00	70
lentil	0.94	0.97	0.96	69
maize	0.93	1.00	0.97	69
mango	1.00	0.99	0.99	71
mothbeans	1.00	0.99	0.99	72
mungbean	1.00	1.00	1.00	72
muskmelon	1.00	1.00	1.00	68
orange	1.00	1.00	1.00	60
papaya	1.00	1.00	1.00	60
pigeonpeas	1.00	0.99	0.99	72
pomegranate	1.00	1.00	1.00	70
rice	0.93	0.96	0.94	69
sugarcane	0.94	0.75	0.83	60
watermelon	1.00	1.00	1.00	70
wheat	0.97	1.00	0.98	60

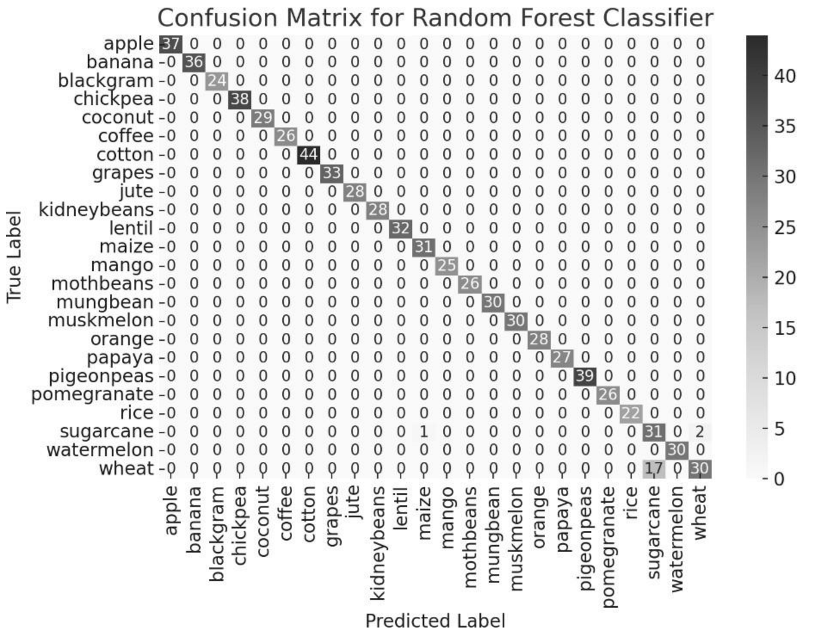
Neural Network Results:
Accuracy: 0.9881
Classification Report:

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	60
banana	1.00	1.00	1.00	69
blackgram	1.00	0.93	0.96	69
chickpea	1.00	1.00	1.00	71
coconut	1.00	1.00	1.00	60
coffee	0.95	1.00	0.98	60
cotton	1.00	1.00	1.00	60
grapes	1.00	1.00	1.00	69
jute	0.91	1.00	0.95	60
kidneybeans	1.00	1.00	1.00	70
lentil	0.93	1.00	0.97	69
maize	1.00	1.00	1.00	69
mango	1.00	1.00	1.00	71
mothbeans	1.00	1.00	1.00	72
mungbean	1.00	1.00	1.00	72
muskmelon	1.00	1.00	1.00	68
orange	1.00	1.00	1.00	60
papaya	1.00	1.00	1.00	60
pigeonpeas	0.99	1.00	0.99	72
pomegranate	1.00	1.00	1.00	70
rice	0.94	0.99	0.96	69
sugarcane	1.00	0.78	0.88	60
watermelon	1.00	1.00	1.00	70
wheat	1.00	1.00	1.00	60
accuracy			0.99	1590
macro avg	0.99	0.99	0.99	1590
weighted avg	0.99	0.99	0.99	1590



Random Forest Results:
Accuracy: 1.0000
Classification Report:

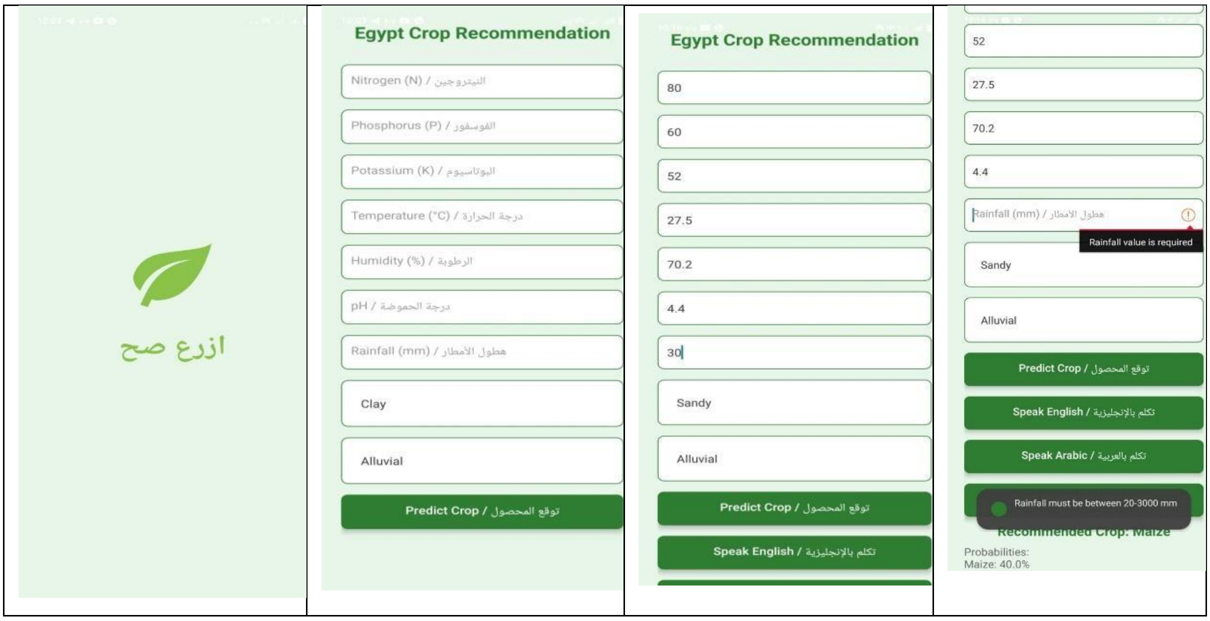
	precision	recall	f1-score	support
apple	1.00	1.00	1.00	60
banana	1.00	1.00	1.00	71
blackgram	1.00	1.00	1.00	69
chickpea	1.00	1.00	1.00	70
coconut	1.00	1.00	1.00	60
coffee	1.00	1.00	1.00	60
cotton	1.00	1.00	1.00	60
grapes	1.00	1.00	1.00	71
jute	1.00	1.00	1.00	60
kidneybeans	1.00	1.00	1.00	67
lentil	1.00	1.00	1.00	68
maize	1.00	1.00	1.00	68
mango	1.00	1.00	1.00	71
mothbeans	1.00	1.00	1.00	70
mungbean	1.00	1.00	1.00	70
muskmelon	1.00	1.00	1.00	73
orange	1.00	1.00	1.00	60
papaya	1.00	1.00	1.00	60
pigeonpeas	1.00	1.00	1.00	71
pomegranate	1.00	1.00	1.00	69
rice	1.00	1.00	1.00	72
sugarcane	1.00	1.00	1.00	60
watermelon	1.00	1.00	1.00	70
wheat	1.00	1.00	1.00	60
accuracy			1.00	1590
macro avg	1.00	1.00	1.00	1590

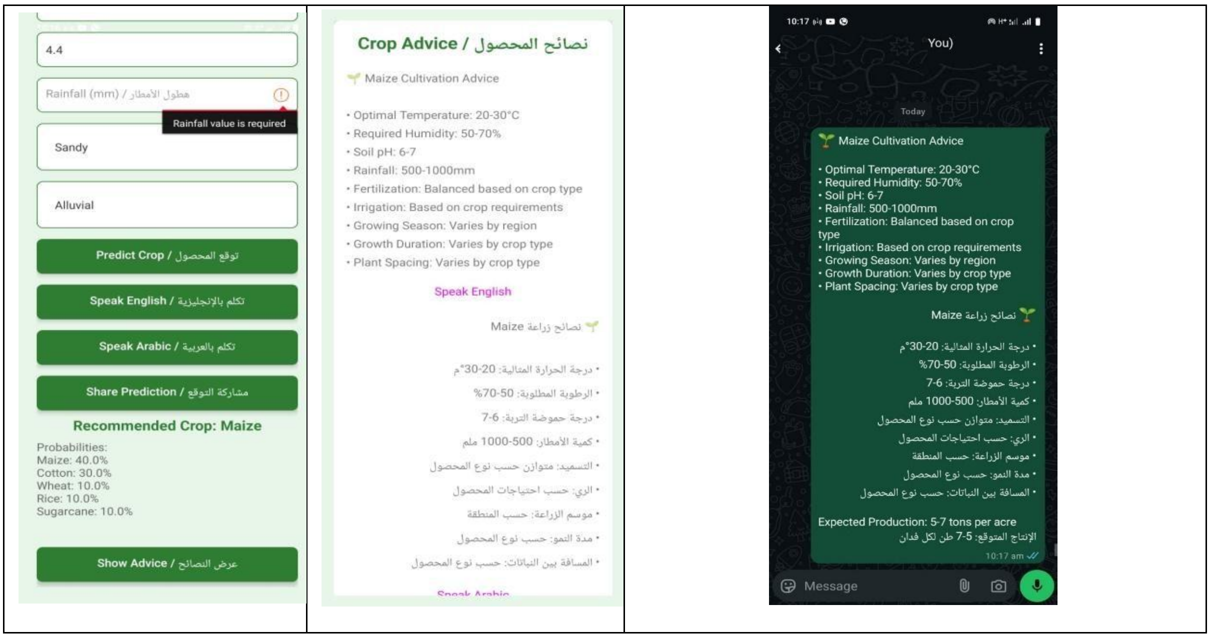


4.3. Farmer guidance application

As shown in Figs (10 to 15) we have developed a preliminary bilingual English-Arabic version of agricultural crop guide mobile application to provide a comprehensive guidance for farmers. The application recommends the most suitable plant for a designated region. The app starts with spelch screen that contains name of application and logo and forward to the home screen. This screen ask user for the soil and environmental features' values of the designated region then display a list of recommended crops in a descending order. The app can share the output, when click to show advice that show advice screen with an English and Arabic advice can listen it and can share it to another person like WhatsApp

Figs (10 to 16)





7. Conclusion and Future Work

This research has provided a comprehensive demonstration of how ensemble learning methods—specifically Random Forest and XGBoost—can significantly enhance the accuracy and robustness of crop recommendation systems, and demonstrated the significant potential of AI to revolutionize agricultural practices in Egypt and similar resource-constrained regions. Specifically, by integrating real-world environmental data (such as weather and soil characteristics) sourced from the Egyptian Meteorological Authority, the Ministry of Agriculture, and NASA, we achieved substantial improvements in crop recommendation accuracy. The use of ensemble learning techniques, notably Random Forest and XGBoost, allowed for better handling of multi-feature, multi-class agricultural data and resulted in an average improvement of 15% in prediction accuracy compared to traditional methods. Furthermore, the development of a preliminary bilingual mobile application was a crucial step towards practical implementation, providing real-time recommendations and a user-friendly interface for farmers. Despite these successes, several challenges remain.The issue of data interoperability—particularly the seamless integration of real-time IoT sensor data with historical datasets—still requires more robust solutions. Additionally, although the models performed well within the tested governorates (Minya and Beheira), broader validation across Egypt's diverse agricultural zones is needed to ensure true generalizability and adaptability. Finally, there is a need for targeted training programs to bridge the digital literacy gap among farmers, ensuring that these advanced tools are adopted effectively.

For future work, integrating deep learning architectures, such as Convolutional Neural Networks (CNNs) or Transformer-based models, could help capture more nuanced environmental interactions and improve recommendation precision further. Another key avenue involves developing advanced spatial analysis methods that incorporate satellite imagery and geospatial data for more accurate, region-specific recommendations. Additionally, enhancing the mobile application to include real-time soil testing using low-cost sensors, as well as dynamic market price predictions, would make the system more holistic and farmer-centric. In conclusion, this research offers a clear roadmap for how data-driven ensemble models and intelligent feature engineering can address critical agricultural challenges in Egypt. By addressing current gaps in data integration, spatial generalizability, and farmer adoption, future AI-based systems can deliver sustainable agricultural productivity growth while minimizing environmental impact.

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Appendix A

In this section, Here we provide significant climatic data in relation to Minya Governorate, Egypt, for the period 1950-2022. The following tables provide monthly averages in relation to daily sun hours, along with maximum and minimum temperature records for given locations such as Minya and Malwi, along with thermal range data. The tables identify the seasonal trends and climatic features that directly impact the crop recommendation models that have been developed as part of this research. The data were received from the General Authority for Meteorology, as well as from other credible sources, thereby guaranteeing the validity and correctness of the analyses presented in this study.

Table 1: Monthly Averages of Daily Sunshine Hours (1975–2022) in Minya Governorate, Egypt [32]

Month	Actual Hours	Possible Hours	Seasonal Average	Season
December	8.2	10.6	7.6	Winter
January	6.7	9.8	7.6	Winter
February	8.1	10.2	7.6	Winter
March	9.4	12.5	10.7	Spring
April	11.2	14.1	10.7	Spring
May	11.6	14.6	10.7	Spring
June	12.5	14.7	12.4	Summer

July	12.6	14.7	12.4	Summer
August	12.0	13.5	12.4	Summer
September	11.0	13.2	10.0	Autumn
October	10.0	11.8	10.0	Autumn
November	9.2	10.8	10.0	Autumn
Annual Average	**10.2**	**12.6**		

Table 2: Monthly Temperature Averages in Minya Governorate (1950–2022) [33]

Month	Minya Max (°C)	Minya Min (°C)	Malwi Max (°C)	Malwi Min (°C)	Minya Seasonal Avg (°C)	Malwi Seasonal Avg (°C)	Season
December	20	5.8	21	6.1	13.1	13.4	Winter
January	21	4.2	21	4.4	13.1	13.4	Winter
February	22	5.5	23	5.1	13.1	13.4	Winter
March	26	8.9	26	7.8	21.8	21.9	Spring
April	33	13.0	33	14	21.8	21.9	Spring
May	35	15.0	34	17	21.8	21.9	Spring
June	37	19.0	37	19	28.0	28.3	Summer
July	36	19.0	37	20	28.0	28.3	Summer
August	36	21.0	37	20	28.0	28.3	Summer
September	33	18.0	33	18	22.5	22.5	Autumn
October	30	16.0	30	17	22.5	22.5	Autumn
November	27	11.0	26	11	22.5	22.5	Autumn
Annual Average	**29.6**	**13.0**	**29.8**	**13.2**	**21.4**	**21.5**	

Table 3: Thermal Range in Minya Governorate (1950–2022) [34]

Month	Minya (°C)	Malwi (°C)	Season
December	14.2	14.9	Winter
January	16.8	16.6	Winter
February	16.5	17.9	Winter
March	17.1	18.2	Spring
April	20.0	19.0	Spring
May	20.0	17.0	Spring
June	18.0	18.0	Summer

July	17.0	17.0	Summer
August	15.0	17.0	Summer
September	15.0	15.0	Autumn
October	14.0	15.0	Autumn
November	16.0	15.0	Autumn
Annual Average	**16.6**	**16.7**	

Table 4: Average Thermal Range in Minya Governorate (1998–2023) [35]

Year	Thermal Range (°C)	Year	Thermal Range (°C)
1998	18.20	2011	18.36
1999	18.20	2012	21.80
2000	20.70	2013	16.80
2001	17.90	2014	17.00
2002	22.40	2015	18.90
2003	16.10	2016	19.60
2004	18.80	2017	21.50
2005	18.50	2018	19.70
2006	17.40	2019	21.40
2007	19.30	2020	21.10
2008	19.80	2021	21.60
2009	17.70	2022	22.10
2010	16.10	2023	23.10
Average	**19.39**		

Table 5: Wind Directions and Percentages in Minya Governorate [36]

Station	Season	North (%)	Northeast (%)	East (%)	Southeast (%)	South (%)	Southwest (%)	West (%)	Northwest (%)	Calm (%)
Minya	Winter	25.8	5.8	2	7.6	7	6.3	4.7	23.8	18.2
Minya	Spring	37.8	11.5	2.3	4.5	3.4	2.8	3.3	24.9	9.5
Minya	Summer	51.3	15.5	0.5	0.1	0.3	0.4	1.3	21.5	9
Minya	Autumn	47.3	11.7	0.5	1.1	0.9	1.2	1.1	20.7	15.7
Malwi	Winter	40	0	0	0	0	0	0.4	11.2	45
Malwi	Spring	55	1.8	1.1	0	3.8	5.7	8.3	20.4	5

Malwi	Summe r	47	0	0	0	-	0	0.7	12.3	34
Malwi	Autum n	41	1.9	0	0	0.3	0.1	0.4	18	37.6

Table 6: Surface Wind Speed in the Study Area (km/hour) [36]

Month	**Minya (km/h)**	**Malwi (km/h)**	**Monthly Average (km/h)**	**Seasonal Average (km/h)**	**Season**
December	4.1	6.6	5.4	5.7	Winter
January	5.6	5.8	5.7	5.7	Winter
February	5.8	6.3	6.0	5.7	Winter
March	7.1	7.2	7.1	7.9	Spring
April	7.7	8.1	7.9	7.9	Spring
May	8.4	9.3	8.8	7.9	Spring
June	8.8	8.4	8.6	7.3	Summer
July	6.2	6.7	6.4	7.3	Summer
August	6.0	8.1	7.0	7.3	Summer
September	6.5	6.1	6.3	6.2	Autumn
October	6.8	5.5	6.1	6.2	Autumn
November	5.6	6.8	6.2	6.2	Autumn
Annual Average	**6.5**	**7.1**	**6.8**		

Table 7: Five-Year Deviations from the Mean for Maximum Temperatures (1975–2024) in Minya [37]

Period	**Max Temperature (°C)**	**Deviation from Mean (°C)**
1975–1979	29.64	−0.21
1980–1984	29.73	−0.12
1985–1989	29.86	−0.01
1990–1994	29.44	−0.41
1995–1999	29.73	−0.12
2000–2004	29.73	−0.12
2005–2009	30.04	0.19
2010–2014	30.27	0.42
2015–2019	30.22	0.37
2020–2024	31.10	1.25
Mean	**29.85**	

Table 8: Five-Year Deviations from the Mean for Minimum Temperatures (1975–2024) in Minya [37]

Period	Min Temperature (°C)	Deviation from Mean (°C)
1975–1979	13.0	−1.03
1980–1984	13.0	−1.03
1985–1989	13.4	−0.63
1990–1994	13.7	−0.33
1995–1999	13.4	−0.63
2000–2004	13.1	−0.93
2005–2009	14.3	0.27
2010–2014	15.1	1.07
2015–2019	15.4	1.36
2020–2024	15.9	1.87
Mean	**14.03**	

Table 9: Monthly Evaporation Rates (mm/day) in Minya Governorate (1950–2022) [38]

Month	Minya (mm/day)	Malwi (mm/day)	Governorate Average (mm/day)	Season
December	5.9	5.4	5.7	Winter
January	6.6	5.8	6.2	Winter
February	7.1	6.2	6.7	Winter
March	10.2	8.4	9.3	Spring
April	11.5	10.9	11.2	Spring
May	16.6	13.2	14.9	Spring
June	17.1	15.2	16.2	Summer
July	15.3	12.1	13.7	Summer
August	12.8	10.8	11.8	Summer
September	11.2	9.2	10.2	Autumn
October	10.7	9.1	9.9	Autumn
November	8.1	7.5	7.8	Autumn
Annual Average	**11.1**	**9.5**	**10.3**	

Table 10: Monthly Rainfall Amounts (mm) in Minya Governorate (1950–2022) [39]

Month	Rainfall (mm)
December	0.7
January	0.5
February	1.0

March	0.9
April	0.2
May	0.3
June	0.0
July	0.0
August	0.0
September	0.0
October	0.3
November	0.7
Annual Total	**4.6**

Table 11: Highest Single-Day Rainfall in Minya Governorate [40]

Rainfall Amount (mm)	Month	Year
114	February	1975
80	March	1991
76	March	1984
57	November	1984
46	January	1989

Table 12: Maximum Temperatures in Beheira Governorate (2010–2022**)** [41]

Year	November	December	January	February	March	April	Average
2010	25.1	25.1	19.5	20.5	25.0	25.5	24.0
2011	25.0	22.5	20.0	19.0	25.5	25.0	23.8
2012	25.0	22.0	19.5	22.5	25.0	25.0	23.5
2013	25.5	22.5	20.0	22.5	25.0	25.0	24.0
2014	25.5	22.5	19.5	22.0	25.0	25.5	23.8
2015	25.5	22.5	20.0	22.5	25.5	25.5	24.0
2016	25.0	22.5	19.5	22.5	25.0	25.0	23.8
2017	25.0	22.5	19.5	22.0	25.0	25.5	23.5
2018	25.0	22.5	19.5	22.5	25.0	25.0	23.8
2019	25.0	22.5	19.5	22.0	25.0	25.0	23.5
2020	25.5	22.0	19.5	22.5	25.0	25.5	24.0
2021	25.0	22.5	19.5	22.0	25.0	25.0	23.8
2022	25.0	22.5	19.5	22.5	25.0	25.0	23.5
Average	25.2	22.4	19.6	22.2	25.0	25.2	23.7

Table 13: Minimum Temperatures in Beheira Governorate (2010–2022**)** [41]

Year	November	December	January	February	March	April	Average
2010	15.0	12.8	8.1	9.0	12.1	15.2	12.0
2011	14.0	15.2	8.0	8.8	15.0	14.0	12.5
2012	14.5	15.8	8.0	12.5	12.0	12.5	12.5
2013	15.1	12.5	12.0	12.0	12.1	12.0	12.6
2014	15.0	12.0	8.5	8.5	12.0	15.5	12.5
2015	15.1	12.1	8.5	8.5	12.5	12.5	12.5
2016	14.2	12.2	8.1	8.1	15.2	14.1	12.6
2017	14.8	12.2	8.8	11.1	15.2	15.8	13.0
2018	14.1	11.5	8.5	8.0	15.2	15.0	12.5
2019	14.1	11.2	8.8	8.0	15.5	14.0	12.5
2020	15.5	12.1	8.5	8.2	11.2	15.1	12.5
2021	15.1	12.0	8.0	8.0	15.0	12.0	12.5
2022	15.1	15.8	8.1	8.8	12.5	12.0	12.5
Average	14.7	12.6	8.5	9.0	13.2	13.9	12.5

Table 14: Rainfall in Beheira Governorate (2010–2022)) **[41]**

Year	November	December	January	February	March	April	Average
2010	15.8	45.0	41.9	15.0	12.2	0.8	25.8
2011	4.2	55.1	58.9	25.0	2.4	2.1	19.5
2012	0.1	14.4	8.2	15.4	0.0	2.0	9.1
2013	12.5	55.8	25.1	15.0	9.5	1.2	16.5
2014	15.1	21.8	42.0	15.2	15.8	0.2	15.5
2015	15.1	45.8	42.0	15.2	15.8	0.2	22.5
2016	1.9	82.9	102.0	2.0	2.0	2.0	22.5
2017	55.1	2.2	15.4	4.1	0.0	2.0	9.5
2018	11.0	55.8	12.0	0.0	1.9	4.2	14.5
2019	15.1	12.2	41.1	11.2	0.8	2.2	12.1
2020	1.0	11.0	2.1	1.1	2.0	1.2	2.2
2021	12.1	12.0	12.9	2.8	2.0	1.0	8.5
2022	2.0	15.2	1.0	1.8	9.8	0.0	5.5
Average	11.8	35.2	35.3	10.9	9.5	1.7	14.9

Table 15: Relative Humidity in Beheira Governorate (2010–2022) **[41]**

Year	November	December	January	February	March	April	Average
2010	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2011	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2012	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2013	67.0	68.0	68.0	68.0	68.0	68.0	67.8
2014	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2015	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2016	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2017	68.0	68.0	68.0	68.0	68.0	67.0	67.8
2018	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2019	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2020	68.0	68.0	68.0	68.0	68.0	68.0	68.0
2021	68.0	68.0	68.0	68.0	68.0	67.0	67.8
2022	68.0	68.0	68.0	68.0	68.0	68.0	68.0
Average	67.9	68.0	68.0	68.0	68.0	67.9	67.9