International Journal of Advanced Computer Research, Vol 13(65)
ISSN (Print): 2249-7277 ISSN (Online): 2277-7970
http://dx.doi.org/10.19101/ IJACR.2023.1362009

Research Article

Intelligent food security model to predict the self-sufficiency status of wheat based on supervised classification algorithms

Mohamed M. Reda Ali[1*], Maryam Hazman[2], Mohamed H. Khafagy[3] and Mostafa Thabet[4]
Assistant Researcher, Faculty of Computers and Artificial Intelligence, Fayoum University, Fayoum, Egypt[1]
Professor, Climate Change Information Center, Renewable Energy, and Expert Systems Agriculture Research Center (ARC), Giza, Egypt[2]
Professor, Faculty of Computers and Artificial Intelligence, Fayoum University, Fayoum, Egypt[3]
Associate Professor, Faculty of Computers and Artificial Intelligence, Fayoum University, Fayoum, Egypt[4]

Received: 31-May-2023; Revised: 01-November-2023; Accepted: 03-November-2023

Abstract
The study presented an intelligent food security (decision support) model to predict the self-sufficiency status of wheat (IFSMPSSW) in Egypt according to food security markers (features) of wheat (FSMW). These markers have the following attributes: region (Reg.), wheat area (WA), yield, wheat production (Prod.), population (Pop.), average per capita of wheat (APCW), other features, and self-sufficiency status of wheat (SSW) as a prediction class. The proposed model utilizes data mining (DM) classification technique and its algorithms such as Naïve Bayes (NB), iterative Dichotomiser 3 (ID3), random forest (RF), and random tree (RT) algorithms to classify and predict the SSW in Egyptian agriculture regions and their governorates. IFSMPSSW aims to support the state of food security of wheat or other crops to close wheat gap and improve the self-sufficiency ratio of wheat (SRW) in Egypt. It supports decision-makers with useful information and recommendations to take appropriate measures and procedures to reduce the wheat insecurity gap in Egypt. These decisions contribute to combating the failure of food supply chains for wheat and food shortage in local and global markets for commerce. Conflicts, natural disasters, high energy prices, or any combination of these affect the global and regional markets and have an effect on the supply chain and the selling price of wheat and other strategic crops. The accuracy of the prediction results for IFSMPSSW by NB, ID3, RF, and RT was the same and reached 92.6%. In 2021, Egypt's self-sufficiency ratio for wheat (SRW) was 48.2% compared to the SRW predicted by the proposed model, which was 69.6%.

Keywords
Intelligent food security model to predict the self-sufficiency status of wheat (IFSMPSSW), Self-sufficiency status of wheat (SSW), Data mining (DM), Food security markers of wheat (FSMW).

1.Introduction
Egypt, along with various developed and developing countries, needs to secure food supplies from strategic grains such as wheat, maize (corn), rice, and soybeans [1, 2]. Consequently, it imports these insufficient crops from global trade markets based on the commodity price lists [3, 4]. In 2021, Egypt's import bill for wheat, maize, and soybeans reached $8 billion USD [5]. The instability of food supply chains in global trade markets, often due to high crop prices or various circumstances, poses significant challenges [6, 7]. It obstructed economic development to achieve targets and the sustainable development goals (SDGs) for developing countries [7, 8]. The food security is defined as, people are able to access food that meets their nutrition needs, and preferences at any time to live a healthy life without any economic pressures and food crisis threats [9–12].

In 2022, 2.4 billion people around the world failed to meet their annual food needs, and 258 million people suffered from high levels of acute food insecurity situation (AFIS) according to integrated food security phases classification (IPC) [2, 10–12]. Where there another critical phases that named chronic food insecurity situation (CFIS), and acute malnutrition situation (AMS) [10–12]. In 2023 there are 25.8

*Author for correspondence

million people in the Democratic Republic of the Congo (DRC) suffered from high levels of AFIS, 24.9 million people in Nigeria, 20.3 million of people in Sudan, 19 million people in Ethiopia, 17 million people in Yemen, 11.9 million people in Bangladesh, 11.8 million people in Pakistan, 6.6 million people in Somalia, and 3 million people in Guatemala [12].

Egypt is ranked 55th and 77th, respectively, out of 113 countries in the global food security index (GFSI) for 2019 and 2022 [13, 14]. Egypt has wheat insecurity problem [1, 15–17], it produces about 9 to 9.84 million tons of wheat during the period from 2018 to 2022 [1, 17–22]. Egypt imports about 10-12 tons from world wheat markets to meet its wheat needs, to reach totally 20-22 million tons of wheat annually for Egyptian population [1] [22–24]. The average per capita of wheat (APCW) for each citizen was 200 kg, Where APCW in 2009 was 145.82 Kg [1, 15, 23, 24]. The study presents an intelligent decision model to predict the self-sufficiency status of wheat (SSW) to support decision makers with informed decision to solve wheat (Crop) insecurity problem. The proposed model named intelligent food security model to predict the self-sufficiency status of wheat (IFSMPSSW) according to food security markers of wheat (FSMW). It utilizes data mining classification technique (DMCT) or machine learning (ML) algorithms to predict the self-sufficiency (SSW) or commodities to support decision makers with informed decisions at right time to take what is necessary to manage and improve the self-sufficiency ratio of wheat (SRW). Where the FSMW have the following features: region (Reg.), wheat area (WA), yield, wheat production (Prod.), population (Pop.), APCW, other features, and SSW.

Data mining (DM) or ML aims to discover useful information, patterns, model, factors or both of them from business dataset(s), data repositories, or database(s) through difference DM techniques such as classification, clustering, regression, anomaly detection [25–27]. ML considers as an artificial intelligence (AI) technique that used to develop intelligent decision model and system to solve the unstructured problems [15, 28, 29].

This study aims to address the wheat insecurity gap in Egypt and seeks to answer the following questions:

- What are the causes for wheat insecurity problem?
- What is the synthesis architecture for the proposed model to predict SSW?
- What are the factors affecting the proposed model?
- How does to the proposed model improve SRW?
- What are the impacts of IFSMPSSW?

The contributions of the study are:

- Collects demographic wheat production and consumption data for agricultural regions governorates from the previous statistics that issued by central agency for public mobilization and statistics in Egypt (CAPMAS) [1, 16, 17, 30-31], economic affair sector (EAS) in ministry of agriculture and land reclamation (MALR) [4, 18, 23], food and agriculture organization (FAO) of the United Nations (UN) [2, 11,13, 22].
- Build the food security of wheat dataset (FSWD) for wheat production and consumption in Egypt.
- Utilize Naïve Bayes (NB), iterative Dichotomiser 3 (ID3), random forest (RF), and random tree (RT) algorithms to predict SSW in Egypt.
- Assumed the APCW for each citizens = 138.53 kg/year (i.e. 95% of APCW in 2009= (145.82x0.95=138.53 kg/citizen).
- Improve SRW through IFSMPSSW in 2021 to reach 70% compared to 48 in current situation in 2021 The accuracy for prediction process results through NB, ID3, RT algorithms was 92.6%. IFSMPSSW improved SRW and reached 69.6 % compared to the reality that was reached 48.2 % in 2021 at Egypt.

This study organizes in six sections as follows, the related works for DM techniques to predict food security or yield for agricultural crops in section two. Section three presents materials and methods. Section four explores results for classification process to prediction SSW in Egypt, and section five explores discussion about research results. Finally, section six summarizes the research conclusions and perspectives.

2.Related works

Reda et al. (2022), have predicted the food security status of wheat (FSSW) by utilizing RT algorithm. The accuracy of their model has reached to 92.3% for predicting the FSSW in agricultural regions and its governorates in Egypt from 2015 to 2020 according to the patterns of wheat production and consumption. Where the dataset of the food security of wheat has had both numerical and nominal data values [15]. Mohamed et al. (2023), have developed a food interest analysis model (FIAM) to identify the preferences food for Twitter users by using ML prediction for preferences and interest's foods for them through 20000 public tweets. The accuracy performance of ML classification algorithms using in their proposed model for users food interests has

been 72.7% for decision tree (DT), 71.8% for support vector machine (SVM), 70.8% for logistic regression (LR), 69% for RF, and 65.5% for NB algorithm [32].
Mamulaidze (2023), have recommended the development of the agricultural sector to improve the self-sufficiency rates of grains to reduce long-term risks and threats to food imports and affect food security for grains, such as the Russia-Ukraine war, the Corona pandemic, or the recovery of high grain prices, shipping, and energy cost, and others challenges [7].

Zeng et al. (2022), have used RF algorithm to predict the soil properties, or soil organic matter as digital soil mapping in Xinxiang city in China to performed spatial distribution for soils according to its soil properties, or other environmental variables. The root mean square error (RMSE) value for their prediction model accuracy through the RF algorithm has been 6.81 and the value of coefficient of determination (R2) has been 0.46, and the mean absolute error (MAE) value has been 5.19 compared to the values of RMSE, R2, and MAE for the trained LSM-ResNet that has reached 6.4, 0.51, and 4.98 respectively [33].

Spandana et al. (2021) have developed model to predict crop yield according to irrigation-plan records, climate and soil conditions through RF algorithm to support decision makers and farmers with an appropriate crop(s) for cultivation in specific agriculture area. Also, their model has supported decision makers and farmers with the required fertilization ratio for cultivation lands according to weather and soil parameters in this area to increase farmer's revenues [34]. Dash et al. (2021), have used SVM and decision tree algorithms to construct a model that predicts the appropriate type of cultivation crop for wheat, rice, and sugarcane based on soil characteristics such as ph and climatic conditions such as rain, humidity, temperature, sunlight, and so on. The accuracy of developed model has been 92% through SVM with linear kernel compared to accuracy for linear SVM and decision tree algorithms [35]

There are two ways to predict agricultural yield that have been used for thirty years: the first method used climate indicators such as (temperature, precipitation, humidity, etc.), and the second method used satellite data that indices to normalized difference vegetation index (NDVI) [36].

There were several crop vegetation health (VH) models for crop(s) yield based on the characteristics of crop vegetation health/ vegetation condition index (VCI) and regional climate parameters / temperature condition index (TCI) such as wheat yield prediction model that developed by Akhand et al. [37], they have used the artificial neural network (ANN) as a ML technique and satellite remote sensing data (SRSD) to predict wheat yield.

Vogitey (2020), have developed an intelligent model to predicted the yield of crop through RF algorithm based on climate change variables to support framers with crop yield production. The accuracy of their prediction results through the smart model has reached 75% to predict crop yield [38]. This study predicts SSW according to the demographic FSMW such as Reg, WA, yield, Prod, APCW and Pop. The attributes of FSWD have nominal values to integrate ID3 algorithm in Weka tool [39].

3.Materials and methods

This paper works utilized ML supervised classification technique to predict the SSW according to wheat production and consumption in Egyptian agriculture regions. The proposed model (IFSMPSSW) utilized DMC algorithms such as NB, ID3, RF, and RT to predict the SSW in Egypt. The FSWD collected from the previous official statistics for Egyptian population and food balance sheets (FBS) of wheat in 2021. This statistics and reports for FBS of wheat, agricultural crops or commodities had been issued by CAPMAS [1, 16, 17, 30, 31], EAS [4, 6, 18, 23], MLAR [40–43], FAO [2, 11, 13, 22], and ministry of supply and internal trade (MSIT) [44, 45]. IFSMPSSW aimed to predict SSW to manage the state of food security for wheat in Egypt at the current and future time according to the patterns of wheat production and consumption in demographic agriculture regions and its Egyptian governorates. Where the targets of IFSMPSSW were:

- Predicting SSW by using DMCT
- Rationalizing wheat import invoice to support the other strategic crop(s) and essential commodities
- Managing the APCW (decrease it / awareness about wheat consumption / healthy consumption)
- Enhancing the SRW
- Supporting the domestic food supply chains with their needs of wheat / strategic crops
- Fighting and mitigating the high prices of grain in the domestic and global markets
- Creating stability for wheat (strategic crop) to support its independency and, its unaffected by external (global) disturbances, conflicts, disasters, diseases, or pandemics.

- Creating stability for strategic grain prices in the local markets
- Achieving the SDGs for the economic development strategy 2030 (EDS2030 / Egypt 2030) in Egypt, and other developing countries.
- Achieving, or supporting the SDGs that determined by UN. Where SDGs could be vulnerable to failure as a result of not achieving food security for strategic crops, which would in turn be reflected in helping its basic pillars to eradicate poverty, hungry, and other goals to achieve sustainable development in the developing countries around the world.

IFSMPSSW aimed to predict SSW and manage its SRW in current and future times according to the research hypothesises, and patterns of demographic wheat production and consumption in agriculture regions and its governorates in Egypt. *Figure 1* illustrates the proposed model (IFSMPSSW) that predicting SSW for demographic agriculture regions in Egypt to reduce wheat gap and enhance its SRW. Where, the proposed model had the following five phases to predict SSW:

Wheat insecurity identification phase: that investigated wheat insecurity situation according wheat production and consumption patterns in demographic agriculture regions (R1, R2, R3, and R4) in Egypt

FSWD phase: that collected data for FMSW to perform classification and prediction for SSW in Egypt.

Machine learning classification (MLC) phase:
Preformed several processes such pre-processing, feature selection, classification, prediction processes to predict SSW in Egypt as the following:

- In pre-processing process, the wheat production and consumption data were collected from several statistical reports issued by several sources, and these data involved both required and non-required information [1, 4, 15–18]. Therefore, the data was filtered to be clear for wheat insecurity situation analysis and processing. The collected data was performed cleaning, normalizing, treating missing values data, or removing its duplications to be distinct to create a FSWD.
- Feature selection process that selected FSMW / attributes from FSWD to predict SSW in Egypt. It divided FSWD into two datasets. The first dataset was named a training data set to learn the ML classifier, and the second dataset was named test dataset to test the validation for the MLC model. Weka tool could split business datasets by many methods such as 10 cross folding method, percentage method (%70, 80%, or another percentage for training, and the remaining percentage for testing classifier mode validation), and other methods.
- MLC process preformed classification for FSWD instances to predict SSW for each recode through MLC algorithms such as NB, RT, ID3 algorithms.

Prediction results for SSW and SRW phase: this phase evaluated the accuracy and prediction results for classification processes for SSW prediction.

Recommendations and decisions phase that provided decision makers in different domain with informed decision and recommendation to manage SRW in Egypt based on the prediction results and expert recommendations.

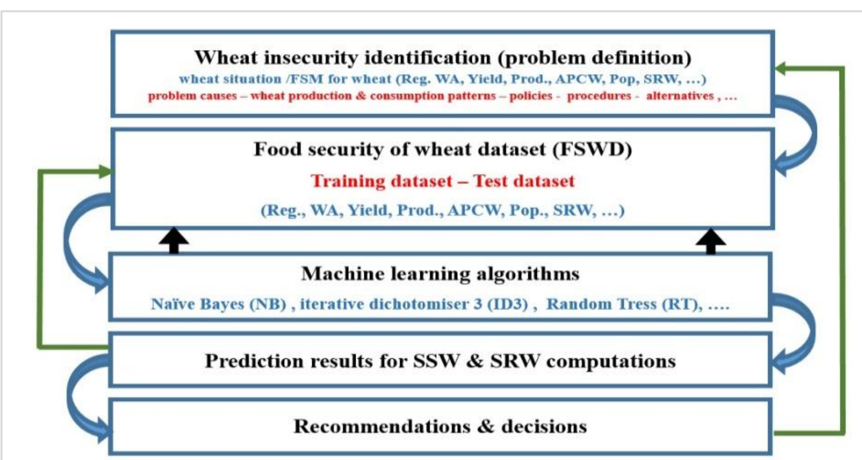

Figure 1 Proposed model to predict SSW in Egypt

3.1Wheat insecurity identification

There was a wheat gap in Egypt because the production of wheat insufficient to meet to Egyptian domestic supply chain with required quantities of wheat in local markets. The quantity of wheat that supplied in Egyptian local markets reached 20.43 million tons in 2021. Egypt imports 12, 14.9, 12.5, 12.9 and 11.1 million tons of wheat from 2017 to 2021 respectively [1, 4, 15–20]. Where, the annual APCW for the previous periods reached more than 200 kg for each person in Egypt [1, 15, 23, 24] compared to the annual global APCW was reached 67.6 Kg/each human [15, 24]. Where, APCW for Egyptian citizen in 2009 was 145.82 kg/person [15]. The WA that cultivated in Egypt from 2017 to 2021 was 1.29 1.33, 1.33, 1.4, and 1.44 million hectares with wheat yield 6.66- 6.9 tons / hectare to produce domestic wheat production equal 8.42, 8.35, 8.56, 9.1, and 9.84 million tons respectively [1, 15–20]. The SRW was equal to the ratio of the quantity of domestic wheat production to the total supply quantity of wheat in local markets. SRW was 34.55%, 35.45%, 40.28%, 41.36%, 48.18% respectively from 2017 to 2021 as shown in *Table 1* for FBS of wheat in Egypt from 2007 to 2021[1,15–20, 23].

The FBS table has the following eight attributes:

- Year: year of FBS
- WA: wheat area - in 1000 feddans
- Prod. : production of Wheat – in 1000 tons
- WI: wheat imports – in 1000 tons
- Pop.: the population (Pop.) in 1000 citizens
- DSQW: domestic supply quantity of wheat – in 1000 tons
- APCW: equal to ((DSQW / Pop.) x 1000) kg.
- SRW: equal to percentage ratio of (prod / DSQW)

Table 1 FBS of wheat in Egypt from 2007 to 2021

Year	WA	Prod.	WI	Pop.	DSQW	APCW	SRW
2007	2716	7379	5916	74828	13790	184.29	53.51%
2008	2920	7977	7381	76651	14546	189.77	54.84%
2009	3179	8523	4061	78522	11450	145.82	74.44%
2010	3066	7169	9805	80443	17685	219.84	40.54%
2011	3059	8371	9804	82410	17153	208.14	48.80%
2012	3182	8795	6561	84418	15782	186.95	55.73%
2013	3401	9460	6785	86460	16678	192.89	56.72%
2014	3414	9280	8105	88530	17825	201.34	52.10%
2015	3472	9608	9409	90624	19563	215.87	49.11%
2016	3353	9345	10820	92737	19592	211.26	47.70%
2017	2922	8421	12025	95203	24374	256	34.55%
2018	3157	8349	14892	97147	23549	242.41	35.45%
2019	3135	8559	12493	98902	21251	212.72	40.28%
2020	3403	9102	12885	100617	22006	218.71	41.36%
2021	3419	9842	11114	102061	20429	200.16	48.18%

In Egypt, the wheat yield from one feedan of clay, valley, or heavy soil = 3.6 – 4.5 tons /feddan, and wheat yield in desert, outside the valley, or sandy soil = 1.8-3.4 tons/feddan [43], the average wheat yield in agriculture strategy 2030 would be reached to 3.25 tons/ feddan [40–43]. The Egyptian government aimed to reclaim 6 million feddans (2.52 hectares) in order to add it to the agricultural area within its vision of sustainable development 2030. Also, it aimed to allocate 30% of these areas for growing strategic crops such as wheat, corn and board beans, to reduce the food gap from these crops and support their food security [41]. *Table 2* and *Figure 2* illustrate the population growth rates (PGR) for Egyptian population from 2019 to 2023 at the middle of years, where the population in million citizens (MC), according to the annual PGR that issued by CAPMAS statistical reports [1, 16, 30, 31].

Based on the previous food security situation of wheat in Egypt, the research had the following two assumptions:

- APCW= 95% of APCW in 2009 = 138.53 Kg/ person yearly
- The yield of wheat = 3.5 tons/feddan,
- PGR = 1.5%
- Wheat consumption people = population volume
- Constant or neglect the other factors

Table 2 Egyptian PGR from 2019 to 2023

Year	2019	2020	2021	2022	2023
Pop	98.9	100.617	102.067	103.6	105.152

Year	2019	2020	2021	2022	2023
PGR	1.74%	1.45%	1.5%	1.5%	1.5%

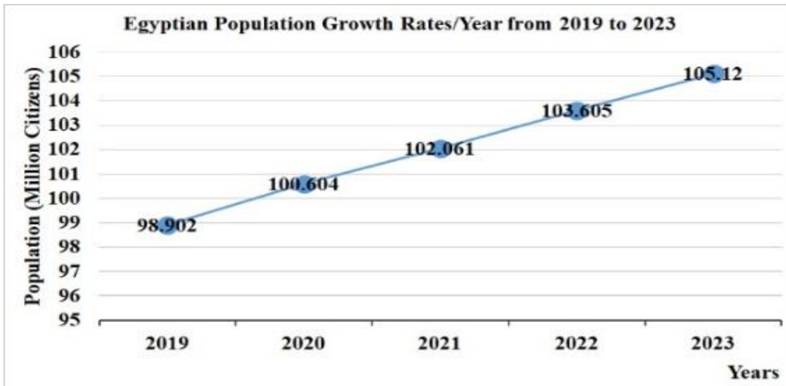

Figure 2 Diagram of Egyptian PGR from 2019 to 2023

3.2Food security of wheat dataset (FSWD)

The FSWD had 27 records to represent wheat production and consumption in Egyptian governorates (cases) in 2021 according to the proposed annual APCW = 138.53 Kg/ citizen. It had following eight attributes (FSMW):

- Gov.: governorate (case)
- Reg: the agriculture region (Reg. = R1, R2, R3, and R4)
- WA: the WA - in 1000 feddans
- Yield: yield of wheat in tons/ feddan,
- Prod.: the production of wheat in1000 tons =WA x yield
- Pop.: the population in 1000 citizens
- Req.W: the required wheat in 1000 tons= APCW x Pop.
- SSW: SSW is the target class that indicated by (Yes / No).

FSWD file was in a comma separated values (CSV) format as shown in *Table 3*. FSWD represented 27 governorates (Cases) for the following four agriculture regions (Reg.):

- R1: was a Reg. in low Egypt region and it's involved 13 governorates.
- R2: was a Reg. in middle Egypt region and it's involved 4 governorates.
- R3: was a Reg. in upper Egypt region and it's involved 5 governorates.
- R4: was a Reg. in out of the Egyptian valley region and it is involved 5 governorates.

Table 3 Sample of FSWD in Egypt to predict SSW

Gov.	Reg.	WA	Yield	Prod.	Pop.	Req. W	SSW
Behera	R1	476.4	2.86	1361	6677	925	Yes
Suez	R1	5.6	2.69	15.1	774	107	No
…….	…	….	…	….	…..	…	….
Giza	R2	33.9	3.05	103	9251	1281	No
Menia	R2	240.9	3.19	769	6078	842	No
…….	…	….	…	….	…..	…	….
Aswan	R3	100	2.58	258	1600	221	Yes
…….	…	….	…	….	…..	…	….
New Valley	R4	254	2.7	689	259	35	Yes
…….	…	….	…	….	…..	…	….

3.2.1Statistic for FSWD

This section had statistics for FSWD such means, variance, data correlation, etc. *Figure 3* illustrates mean, standard deviation measures for Yield attribute in FSWD.

The attributes correlation for FSWD illustrates in *Figure 4* by using correlation ranking filter (CRF).

3.2.2Data pre-processing and feature selection

Transforming the values of FSMW in *Table 3* for FSWD form numerical format to nominal format as shown in *Table 4* based on the following research assumptions:

- APCW= 95% of APCW in 2009 = 138.53 Kg/year.
- Region (Reg): was an agriculture region in Egypt that involved four regions in nominal values (R1, R2, R3, R4) that involved 27 governorates /cases.
- WA: was a wheat grown area in feddans (i.e. one hectare = 2.38 feddans), it had the following nominal values:
- HA: was high (large) WA (i.e. one wheat feddan serve less than 20 citizens)
- MA: was a medium area (i.e. one wheat feddan serve from 20 to 40 citizens)
- LA: was a low area (i.e. one wheat feddan serve from more than 40 citizens).

- Yield: was wheat productivity unit from one feddan, it had the following nominal values:
  - Normal: was a normal yield when wheat productivity unit >= 1.8 tonnes /feddans.
  - Low: was a Low yield when wheat productivity unit < 1.8 tonnes /feddans.
- Population (Pop): was a population in MC, it had the following nominal values:
  - Pop = HP if (Pop > 4 MC)
  - Pop = MP if (1MC<= Pop < =4 MC)
  - Pop = LP if (Pop < 1MC)
- SSW: was a self-sufficiency ratio of wheat in Egypt.
  - SSW = yes if (production >= Req. W)
  - SSW= no if (production < Req. W)

Table 4 explores FSWD with nominal values to represent wheat production and consumption in Egyptian agriculture regions in 2021 to predict SSW through the classification algorithm such as NB and ID3 algorithms. Where the format of FSWD was in a CSV and its attributes had nominal values to upload it in Weka tool to visualize it in 2-D graphs to select the required features for classification process as shown *Figure 5.*

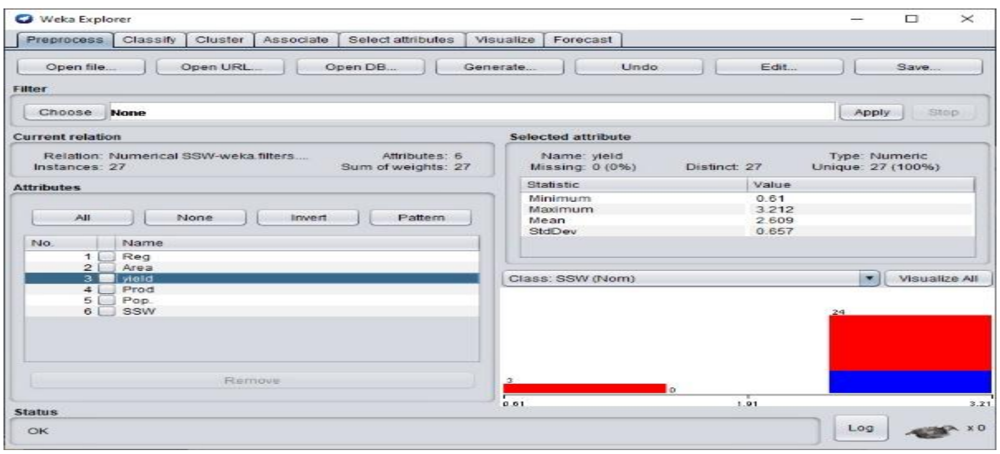

Figure 3 The mean and SD for yield attribute in FSWD

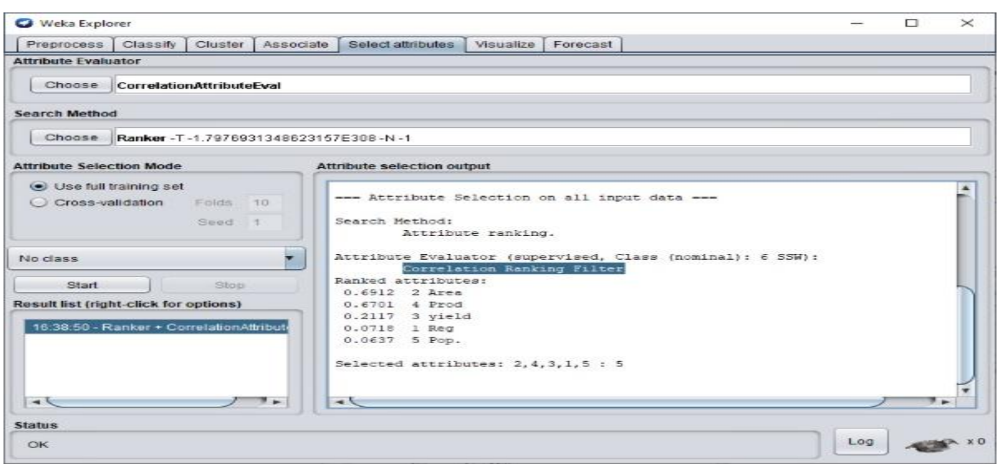

Figure 4 Data correlation for FSWD

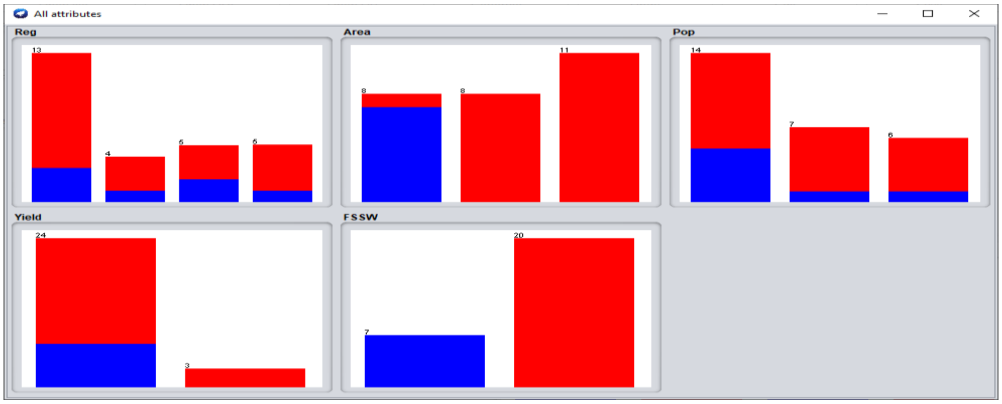

Figure 5 The visualizations for features of FSWD

Table 4 FSWD in 2021 at Egypt

Cases	Reg	WA	Pop	Yield	SSW
C1	R1	HA	HP	Normal	Yes
C2	R1	HA	HP	Normal	Yes
C3	R1	MA	HP	Normal	No
C4	R2	MA	HP	Normal	No
C5	R2	HA	HP	Normal	Yes
C6	R1	HA	HP	Normal	Yes
C7	R3	HA	HP	Normal	Yes
C8	R3	MA	HP	Normal	No
C9	R4	HA	LP	Normal	yes
C10	R1	LA	HP	Normal	No
C11	R1	MA	HP	Normal	No
C12	R2	MA	MP	Normal	No
C13	R3	MA	MP	Normal	No
C14	R1	LA	HP	Normal	No
C15	R3	HA	MP	Normal	Yes
C16	R1	LA	HP	Normal	No
C17	R2	LA	HP	Normal	No
C18	R1	LA	MP	Normal	No
C19	R4	HA	LP	Low	No
C20	R1	MA	MP	Normal	No
C21	R3	MA	MP	Normal	No
C22	R1	LA	LP	Normal	No
C23	R4	LA	LP	Low	No
C24	R4	LA	LP	Low	No
C25	R1	LA	LP	Normal	No
C26	R4	LA	LP	Normal	No
C27	R1	LA	HP	Normal	No

These features were used to build the classification model through learning data sets to learn the classifier model to predict SSW for unknown instances in test dataset of FSWD through classification algorithms such as NB, RT, ID3 algorithms. To spilt FSWD, we used 10-fold cross validation in Weka tool to select randomly 90% of FSWD as a training dataset. The remaining 10% was used as a test dataset to test model validation. Also, we can split FSWD to percentages 70% or 60%, or other parentage as a training dataset and the reaming data to test classifier as shown *Figure 6*.

3.3Implementation and deployment

This section involved three sub-sections to predict SSW through NB, ID3, RF, and RT algorithms in Weka tool that visualized FSWD features and instances as shown in *Figures 3* and *5*. The first sub-section explored the prediction process for SSW through NB algorithm, while the ID3 classification was explored in second subsection. Finally, a test case for classification the FSWD was introduced in the third sub-section.

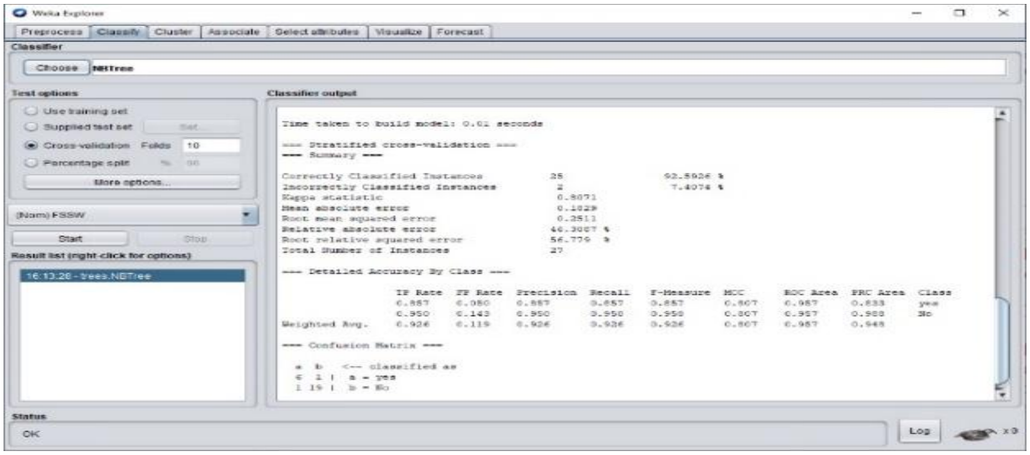

Figure 6 Methods to split FSWD

3.3.1SSW classification through NB algorithm

The first phase of NB algorithm was for training the model to predict SSW class. It computed the membership probabilities for FSWD instances as shown in Equation 1 [4, 5, 16]. The true prediction class result for C_i(SSW) that indicated by C_1= (SSW = "Yes") = 7 and False prediction class result for SSW that indicated by C_2= (SSW = "No") = 20.

$$P(C_i / X) = \frac{P(X \backslash c_i)p(c_i)}{p(X)} \quad (1)$$

Where, P(c|x) was the posterior probability of class given predictor (target attribute = SSW), P(c) was the prior probability of class, P(x|c) was the probability of the predictor given class (attribute values), and P(x) was the prior probability of predictor [25–27, 46]. In the second phase, the model was tested. the NB positive and negative probabilities were checked to determine the prediction result for given fact or tuple X. Therefore, NB classifier predicted SSW = No for tuple X, *If* (SSW=Yes–_/ X) < P (SSW =No/X), otherwise predicted SSW = No for tuple X.

3.3.1.1 Learning phase for NB algorithm

In this phase, the membership probabilities for FSWD features were computed based on prediction results for SSW class (Yes /No) in *Table 5* to calculate prior probabilities, and through the values of Reg. in *Table 6*, area in *Table 7*, Pop. in *Table 8*, and Yield in *Table 9* to calculate posterior probabilities. Where the following five steps were used to predict SSW based on NB classifier [25–27, 46]:

1. Calculating the prior probabilities for SSW labels
2. Calculating posterior probabilities of each attribute for SSW
3. Multiplying posterior probabilities (conditional probability) for same class in step 2
4. Multiplying prior and posterior probabilities in steps 1and 3
5. Determining which class had higher probability P(Yes/X) or (No/X) to indicate for predicting results Yes or No.

Table 5 Probability of SSW or C_i (C_1= yes / C_2= No)

SSW	**N(C_i=Yes /No)**	**P(C_i =Yes/No)**
Yes	7	7/27 = 0.26
No	20	20/27 = 0.74
Total (N)	27	

Table 6 NB predictions for SSW through region

Re	**SSW=Ye**	**P(Reg/Yes**	**SSW=N**	**P(Reg/No)**
R1	3	3/7 = 0.43	10	10/ 20 =
R2	1	1/7 = 0.14	3	3/20 =
R3	2	2/7 = 0.29	3	3/20 =
R4	7	1/7 = 0.14	4	4 / 20 = 0.2

Table 7 NB predictions for SSW through WA

W	**SSW=Ye**	**P(WA/Yes**	**SSW=N**	**P(WA/No)**
HA	7	7/7= 1	10	1/20 = 0.05
MA	0	0/7 =0	4	11/20 =
LA	0	0/7 =0	4	8/20 = 0.4

Table 8 NB predictions for SSW through population

W	**SSW=Ye**	**P(Pop/Yes**	**SSW=N**	**P(Pop/No)**
HP	5	5/7 =	9	1/20 = 0.45
MP	1	1/7 =	5	11/20 =
LP	1	1/7 =	6	8/20 = 0.3

Table 9 NB predictions for SSW through yield

Yiel	**SSW=Y**	**P(Yield/Ye**	**SSW=N**	**P(Yield/N**
HP	7	7/7 = 1	17	17/20 =
LP	0	0/7 = 0	3	3/20 =

3.3.1.2 Test phase for NB algorithm

Two test cases were applied to predict SSW (x) is (Yes) or (No) as follows:

3.3.1.2.1 Case 1 to predict SSW:

We predicted the SSW (x) which was (Yes) or (No) for unknown instance x, If x = (Reg.=R2, Pop= HP, WA=HA, Yield=Normal)

Firstly, we calculated the $\mathbf{C_1}$ and C_2 for x as following where x instance values are: Reg.=R2, Pop=HP, WA=HA, Yield=Normal:

NB predictions for $\mathbf{C_1}$ or (SSW = Yes) through the values of Reg., WA, Pop, and yield

P(Yes/X) = [P(R2/yes) x P(HP /yes) x P(HA /yes) P(Normal /yes)] / P(SSW=yes)=

P (Reg=R2 \ SSW=Yes) = 1/7 = 0.14

P (Pop. = HP \ SSW=Yes) = 5/7= 0.714

P (WA=HA \ SSW=Yes) = 7/7= 1

P (Yield=*Normal* \ SSW=Yes) =7/7= 1

P (SSW=Yes) = 7/27 = 0 .259

0.14 x 0.714 x 1 x 1 x 0.259 = 0.026

NB predictions for $\mathbf{C_2}$ or (SSW = No) through the values of Reg., WA, Pop, and yield

P(No/X) = [P(R2/No) x P(HP /No) x P(HA /No) x P(Normal /No)] / P(SSW=No) =

P (Reg=R2 \ SSW=NO) = 3/20 = 0.15

P (Pop. = HP \ SSW=No) = 9/20= 0.45

P (WA=HA \ SSW=No) = 1/20= 0.05

P (Yield=*Normal* \ SSW=No) =17/20= 0.85

P (SSW=NO) = 20/27 = 0 .74

0.15 x 0.45 x 0.05 x 0.85 x 0.74 = 0.0021

Secondly we predicted the SSW(x) class as following:

SSW(x) = Yes for tuple X if P(Yes/X) > P(No/X)

SSW(x) = No for tuple X if P(Yes/X) < P(No/X)

Therefore, NB classifier predicts SSW = Yes for tuple X, where P(Yes /X) > P(No/X)

3.3.1.2.2 Case 2 to predict SSW:

We predicted the SSW (x) which was (Yes) or (No) for unknown the instance x, If x = (Reg.=R4, Pop= LP, WA=LA, Yield=Low)

Firstly, we calculated the $\mathbf{C_1}$ and C_2 for x as following where x instance values are: Reg.=R4, Pop=LP, WA=LA, Yield=Low.

NB predictions for $\mathbf{C_1}$ or (SSW = Yes) through the values of Reg., WA, Pop, and yield

P(Yes/X) = P(R4/yes) x P(LP /yes) x P(LA /yes) x P(Low/yes) x P(SSW=yes) =

P (Reg=R4 \ SSW=Yes) = 1/7 = 0.143

P (Pop. = HP \ SSW=Yes) = 1/7= 0.143

P (WA=HA \ SSW=Yes) = 0/7= 0

P (Yield=*Normal* \ SSW=Yes) =0/7= 0

P (SSW=Yes) = 7/27 = 0 .259

0.143 x 0.143 x 0 x 0 x 0.259 =0

NB predictions for $\mathbf{C_2}$ or (SSW = No) through the values of Reg, WA, Pop, and yield

P(No/X) = [P(R4/No) x P(LP /No) x P(LA /No) x P(Low /No)] / P(SSW=No) =

P (Reg=R4 \ SSW=NO) = 4/20 = 0.2

P (Pop. = LP \ SSW=No) = 6/20= 0.3

P (WA=LA \ SSW=No) = 8/20= 0.4

P (Yield=*Low* \ SSW=No) =3/20= 0.15

P (SSW=NO) = 20/27 = 0 .74

0.2 x 0.3 x 0.4 x 0.15 x 0.74 =0.0027

Secondly we predicted the SSW(x) class as following:

SSW(x) = Yes for tuple X if P(Yes/X) > P(No/X)

SSW(x) = No for tuple X if P(Yes/X) < P(No/X)

Therefore, NB classifier predicts SSW = No for tuple X, where P(No/X) > P(Yes /X)

3.3.2SSW classification through ID3 algorithm

The following steps are used for drawing and pruning decision tree diagram for SSW by ID3 algorithm:

- Calculating Entropy (S) for FSWD.
- Calculating Entropy (S) and information gain (Gain) for each attribute in FSWD
- Selecting the attribute has a maximum Gain to be root node for ID3 tree for SSW classification.
- Repeating the step b and c for the remaining attributes to drawing subtrees and stop when Gain = S

FSWD had four attributes as shown in *Table 4*: Reg, WA, Pop, and Yield which were used to calculate Entropy (S) and Gain for each individual attribute in the dataset as follows:

A. Computing Entropy (S) for the attributes of FSWD to measure attribute probability for predicting class that had two statuses (Yes / No) as shown in Equation 2. Where, FSWD has 7 tuples (cases) of SSW= yes (+) and 20 cases of SSW= No (-),

S = [7+, 20-]

$$Entropy\ (S) = -\frac{P}{P+n} log_2 \frac{p}{p+n} - \frac{n}{P+n} log_2 \frac{n}{P+n} \quad (2)$$

$$Entropy\ (S) = -\frac{7}{27} log_2 \frac{7}{27} - \frac{20}{27} log_2 \frac{20}{27} = 0.8256 \quad (3)$$

B. Computing Entropy (S_{Reg}) and Gain for first attribute that named: region (Reg) as shown in *Table 10* and information gain in Equation 3. The values of Reg. were R1, R2, R3, R4

The information Gain (S, Pop) equalled the Entropy (S) for SSW subtract to the summation of region Entropies (Sv) that represented the probabilities of region values (R1, R2, R3, R4) to SSW to represent Gain (S, Reg) as shown in Equation 3.

Table 10 SSW= (Yes/No) prediction for region

Reg.	SSW= Yes (+)	SSW=No (-)
1	3 / 7 = 0.43	10 / 20 = 0.5
R2	1 / 7 = 0.14	3 / 20 = 0.15
R3	2 / 7 = 0.29	3 / 20 = 0.15
R4	1 / 7 = 0.14	4 / 20 = 0.2

$S_{R1} \leftarrow [3+,10-]$

$\text{Entropy}\ (S_{R1}) = -\frac{3}{13}\log_2\frac{3}{13} - \frac{10}{13}\log_2\frac{10}{13}$ =0.779

$S_{R2} \leftarrow [1+, 3-]$

$\text{Entropy}\ (S_{R2}) = -\frac{1}{4}\log_2\frac{1}{4} - \frac{3}{4}\log_2\frac{3}{4} = 0.811$

$S_{R3} \leftarrow [2+, 3-]$

$\text{Entropy}\ (S_{R3}) = -\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5} = 0.970$

$S_{R4} \leftarrow [1+, 4-]$

$\text{Entropy}\ (S_{R4}) = -\frac{1}{5}\log_2\frac{1}{5} - \frac{4}{5}\log_2\frac{4}{5} = 0.721$

$$Gain(S, Reg) = Entropy(S) - \sum_{v \in (R_1,R_2,R_3,R_4)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (3)$$

Gain (S, Reg) = 0.82 - 0.37 - 0.12 – 0.17 -0.13 = 0.0167

C. Computing Entropy (S_{WA}) and Gian for second attribute that named: WA, as shown in *Table 11*, and information gain in Equation 4. The values of WA were HA, MA, LA.

The Gain (S, WA) equalled the Entropy (S) for SSW subtract to the summation of WA Entropies (Sv) that represented the probabilities of WA values (HA, MA, LA) to SSW to represent *Gain (S, WA)* as shown in Equation 4.

Table 11 SSW= (Yes/No) prediction for WA

WA	SSW= Yes (+)	SSW=No (-)
HA	7/7 = 1	1/ 20 = 0.05
MA	0/ 7= 0	8 / 20 = 0.4
LA	0 / 7= 0	11 / 20 = 0.55

$S_{HA} \leftarrow [7+, 1-]$

$Entropy\ (S_{HA}) = -\frac{7}{8}log_2\frac{7}{8} - \frac{1}{8}log_2\frac{1}{8}$ =0.543

$S_{MA} \leftarrow [0+, 8-]$ $\quad Entropy\ (S_{MA}) = 0$

$S_{LA} \leftarrow [0+,11-]$ $\quad Entropy\ (S_{LA}) = 0$

$$Gain(S,WA) = Entropy(S) - \sum_{v \in (HA,MA,LA)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (4)$$

$$Gain(S,WA) = Entropy(S) - \frac{8}{27} Entropy(S_{HA})$$

Gain (S, WA) = 0.826 - 0.16 - 0 - 0 = 0.665

D. Computing Entropy (S_{Pop}) and Gian for third attribute that named: population (Pop), as shown in *Table 12*, and information gain in Equation 5. The values of Pop. were HP, MP, LP

The Gain (S, Pop) equalled the Entropy (S) for SSW subtract to the summation of population Entropies (Sv) that represented the probabilities of population values (HP, MP, LP) to SSW to represent Gain (S, Pop) as shown in Equation 5.

Table 12 SSW= (Yes/No) prediction for Pop

Pop	SSW= Yes (+)	SSW=No (-)
HP	5 / 7 = 0.714	9/ 20 = 0.45
MP	1 / 7= 0.143	5 / 20 = 0.25
LP	1 / 7= 0.143	6 / 20 = 0.3

$S_{HP} \leftarrow [5+, 9-]$

$\text{Entropy}\ (S_{HP}) = -\frac{5}{14}\log_2\frac{5}{14} - \frac{9}{14}\log_2\frac{9}{14}$ =0.940

$S_{MP} \leftarrow [1+, 5-]$

$\text{Entropy}\ (S_{MP}) = -\frac{1}{6}\log_2\frac{1}{6} - \frac{5}{6}\log_2\frac{5}{6} =$ 0.65

$S_{LP} \leftarrow [1+,6-]$

$$\text{Entropy}\ (S_{LP}) = -\frac{1}{7}\log_2\frac{1}{7} - \frac{6}{7}\log_2\frac{6}{7} = 0.591$$

$$Gain(S, Pop) = Entropy(S) - \sum_{v \in (HP,MP,LP)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (5)$$

$$Gain(S, Pop) = Entropy(S) - \frac{14}{27} Entropy(S_{HP}) - \frac{6}{27} Entropy(S_{MP}) - \frac{7}{27} Entropy(S_{LP})$$

Gain (S, Pop.) = 0.826 – 0.487 – 0.144 – 0.153 = 0.04

E. Computing Entropy (S_{Yield}) and Gain for fourth attribute that named: yield, as shown in *Table 13*, and information Gain in Equation 6. The values of Yield were Normal and Low

The information Gain (S, Yield) equalled the Entropy (S) for SSW subtract to the summation of yield Entropies (Sv) that represented the probabilities of yield values (Normal, Low) to SSW to represent *Gain (S, Yield)* as shown in Equation 6.

Table 13 SSW= (Yes/No) prediction for Yield

Yield	SSW= Yes (+)	SSW=No (-)
Normal	7 / 7 = 1	17 / 20 = 0.85
Low	0 / 7= 0	3 / 20 = 0.15

$S_{Normal} \leftarrow$ [7+,17-]

$Entropy\ (S_{Normal}) = -\frac{7}{24} log_2 \frac{7}{24} - \frac{17}{24} log_2 \frac{17}{24}$ =0.870

$S_{Low} \leftarrow$ [0+, 3-] $Entropy\ (S_{Low}) = 0$

$$Gain(S,Yield) = Entropy(S) - \sum_{v \in (Normal,Low)} \frac{|S_v|}{|S|} Entropy(S_v) \quad (6)$$

$$Gain(S,Yield) = Entropy(S) - \frac{24}{27} Entropy(S_{Normal})$$

Gain (S, Yield) = 0.826 – 0.774 – 0 = 0.052

F. Selecting attribute of maximum Gain value as a root node (RN)
Gain (S, WA) = 0.665
Gain (S, Reg) = 0.017
Gain (S, Pop.) = 0.04
Gain (S, Yield) = 0.052
RN is WA

G. The values of attribute of the same prediction status (Yes or No) was an end leaf as shown in *Tables 14 and 15*, and otherwise considering it a child pruning node for decision tree that required to classify and calculate the previous steps for sub trees of *Table 16* tuples.

Table 14 SSW prediction for WA = MA

Cases	Reg	Pop	Yield	SSW
C3	R1	HP	Normal	No
C11	R1	HP	Normal	No
C4	R2	HP	Normal	No
C8	R3	HP	Normal	No
C20	R1	MP	Normal	No
C12	R2	MP	Normal	No
C13	R3	MP	Normal	No
C21	R3	MP	Normal	No
C3	R1	HP	Normal	No

Table 15 SSW prediction for WA = LA

Cases	Reg	Pop	Yield	SSW
C23	R4	LP	Low	No
C24	R4	LP	Low	No
C10	R1	HP	Normal	No
C14	R1	HP	Normal	No
C16	R1	HP	Normal	No
C27	R1	HP	Normal	No
C17	R2	HP	Normal	No
C22	R1	LP	Normal	No
C25	R1	LP	Normal	No
C26	R4	LP	Normal	No
C18	R1	MP	Normal	No

Table 16 SSW prediction for WA = HA

Cases	Reg	Pop	Yield	SSW
C19	R4	LP	Low	No
C1	R1	HP	Normal	yes
C2	R1	HP	Normal	yes
C6	R1	HP	Normal	yes
C5	R2	HP	Normal	yes
C7	R3	HP	Normal	yes
C9	R4	LP	Normal	yes
C15	R3	MP	Normal	yes
C15	R3	MP	Normal	yes

H. Going to next phase to repeat the previous steps for classifying the other tuples. Otherwise, stopping and end decision tree as shown in *Figure 3*.

3.3.3FSWD classification

The FSWD was used for predicting the SSW by using RF, RT, NB, and ID3 algorithms in Weka tool. The result for RF and RT is shown *Figure 7*. *Figure 8* illustrates the decision tree diagram for prediction process of SSW.

The Equations from 7 to 10 extracted from *Figure 8* to predict SSW in democratic agriculture region in Egypt to support decision maker to manage the food security situation for wheat and take appropriate procedures and decisions.

If Reg = (R1v R2 v R3), WA = HA→ SSW = Yes (7)

If Reg = R4, WA = HA, Yield = Normal → SSW = Yes (8)

If Reg = R4, WA = HA, Yield = Low→ SSW = No (9)

If WA = (MA v LA) → SSW = No (10)

4.Classification results to predict SSW

This section had two sub-sections to explore the results of MLC process to predict SSW for FSWD instances in the first sub-section, and the situation of SRW in the second sub-section.

4.1Prediction results

The confusion matrix recognition functions evaluated prediction results for SSW based on the retrieval information for true positive (TP), false positive (FP), false negative (FN), and true negative (TN) of predictions results. Where, the prediction results [15, 25–28] for the previous algorithms had the same information for TP=6, FP=1, FN=1, and TN=19 to compute precision, recall, and prediction process accuracy that quailed to 92.6% for the NB, ID3, RF, and RT algorithms as shown in *Table 17* by Equations 11to14. Where the precision is equal to the ratio of retrieval TP to the summation of TP and FP instances as shown in Equation 11.

Precision = TP /(TP+FP) =6/7 = 85.7% (11)

The recall was equal to the ratio of retrieval TP to the summation of TP and FN instances as shown in Equation 12.

Recall= TP / (TP+FN) = 6/7= 85.7% (12)

The prediction accuracy was equal to the ratio of retrieval summation of TP and TN to the summation of all retrieval instances as shown in Equation 13.

Accuracy = (Tp +TN)/(TP+FP+ FN+ TN) = 25/27= 92.6% (13)

Equation 14 computed F1 score (F-measure) to evaluate the performance of ML model based on its precision and recall.

F1= 2x Precision x Recall / (Precision + Recall) = (2x 0.857 x 0.857) / (0.857 + 0.857) =0.857 (14)

Table 17 Results of MLC algorithms to predict SSW

Item	**MLC Algorithms**			
	NB	**ID3**	**RT**	**RF**
Tp	6	6	6	6
Fp	1	1	1	1
FN	1	1	1	1
TN	19	19	19	19
Total Instances	27	27	27	27
Precision	0.857	0.857	0.857	0.857
Recall	0.857	0.857	0.857	0.857
Accuracy	92.6%	92.6%	92.6%	92.6%
F1	0.857	0.857	0.857	0.857

4.2The scenarios of SRW in Egypt

IFSMPSSW improved the SRW in current and future situations from 2021 to 2030 as shown in *Table 18*, according to the annual real APCW = 200 Kg. /Person, and MLAR APCW = 153 kg/ person, and the proposed APCW = 138.53 Kg. /person. *Table 19* has illustrated comparative study between the contributions of IFSMPSSW and previous works according to regional, demographic, global position system (GPS) for wheat or crop(s) area, interest with high wheat (crop) yield and production, APCW, and PGR to mitigate hunger and poverty crises, global grains prices.

Table 18 Situations of SRW in Egypt from 2021-30

Items	**Real Wheat Situation in 2021**	**Proposed wheat situation in 2021**	**MALR SDGs in 2030**	**IFSMPSSW in 2030**
Year	2021	2021	2030	2030
WA	3.42	3.42	3.75	4.4
Yield	2.88	2.88	3.25	3.5
Prod.	9.84	9.84	12.2	15.4
DSQW / (Req W.)	20.43	14.14	20.3	15.81
Pop.	102.061	102.061	116.67	116.67
APCW	200	138.53	174	138.53
SRW	48.2%	69.6%	60%	97.4%

Table 19 A comparative study between IFSMPSSW and previous works

No.	**Items**	**IFSMPSSW**	**Mohamed et al. [33]**	**Zeng et al. [35]**	**Spandana et al. [36]**	**Dash et al. [37]**	**Akhand et al. [39]**	**Vogiety [40]**
1	Regional /demographic wheat (crop) area (large / limited / No)	Large	No	Limited	Limited	Limited	Limited	Limited
2	High wheat/ crop yield interest	Yes	No	No	Yes	Yes	Yes	Yes
3	High wheat /crop production interest	Yes	No	No	Yes	Yes	Yes	Yes
4	Interest by PGR	Yes	No	No	No	No	No	No
5	Interest by APCW	Yes	No	No	No	No	No	No
6	Crop importance {strategic (St.) – profit (Pro) – /preference (Pref) / other (---)}	St	Pref.	---	Pro.	Pro.	Pro.	Pro.
7	Use modern agro techniques and technologies	Yes	---	---	---	---	---	---

No.	Items	IFSMPSSW	Mohamed et al. [33]	Zeng et al. [35]	Spandana et al. [36]	Dash et al. [37]	Akhand et al. [39]	Vogiety [40]
8	More investment projects /jobs	Yes	No	No	No	No	No	No
9	Support AI and ML techniques	Yes	Yes	Yes	Yes	Yes	Yes	Yes
10	Support smallholders clustering	Yes	---	---	---	---	---	---
11	Support resources integration	Yes	No	Yes	Yes	Yes	Yes	Yes
12	Support regional wheat integration	Yes	---	---	---	---	---	---
13	Support national / personal incomes	Yes	No	No	Yes	Yes	Yes	Yes
14	Recommends climate and soil features	Yes	No	No	Yes	Yes	Yes	Yes
15	Support SDGs (global / local)	Yes	No	No	No	No	No	No
16	Fair wheat /crop price for all	Yes	---	---	No	No	No	No
17	Mitigate global grains prices	Yes	No	No	No	No	No	No
18	Support high living style	Yes	No	No	Yes	Yes	Yes	Yes
19	Mitigate hunger and poverty crises	Yes	No	No	No	No	No	No
20	Support regional food security status of Crop / wheat (SSW)	Yes	No	No	No	No	No	No
21	Close crop insecurity gap (SRW)	Yes	No	No	No	No	No	No
22	Apply the agriculture rotation / cycle	Yes	No	No	---	---	---	---
23	Interest by integrated industries	Yes	No	No	No	No	No	No

5.Discussion

According to the research results, the accuracy of the prediction process of IFSMPSSW was reached 92.6% through NB, ID3, RF, and RT algorithms. Also the SRW for IFSMPSSW reached 69.6% compared to 48.2% for wheat situation in reality to close wheat gap in Egypt. The following three sub-sections explore the impacts of research in the first sub-section, and the limitations of research in the second sub-section. Finally, the research recommendations are found in the third sub-section.

5.1The research impacts

The most important impacts, effects, or advantages of the proposed model (IFSMPSSW) are as the following:

- Develop model to predict SSW or other cop(s) in current and future times
- Support decision makers with informed decisions agriculture, food security, industrial domains to manage and improve SRW, self-sufficiency ratio of for other crop(s).
- Integrate a ML technique(s) to predict SSW or other crop(s).
- Present a conceptual vision through IFSMPSSW to manage the food security state for strategic crop(s) in development countries to achieve SDGs.
- Present patterns for demographic crop production and consumption.
- Present FSMW to predict SSW through ML classification process
- Create more investment projects and jobs to eradication of unemployment, poverty, and hunger to raise the standard of living.
- Integrate nation resources
- Rationalize crop(s) imports to save time and cost.
- Encourage wheat (crop) cultivation in large sectors by using modern agriculture technology and techniques
- Remove hungry by reducing wheat (crop) security gap
- Help developing countries to fight the instability of wheat prices in local and global grain markets at crisis times.
- Support and achieve SDGs
- Success can be achieved toward intelligent food security and smart agriculture.

5.2The Research limitations and barriers

- It needs adoption from the Egyptian government, UN organizations, and other international organizations that aim to achieve sustainable development and eradicate poverty and hunger.
- It needs to establish unified large entities for micro-agricultural investments to create a unified food security database(s)/ repositories to manage the millions of agricultural tenures (small holds) that do not follow the agricultural rotation. Also, crops grow in large sectors.

- It requires unifying and coordinating the capabilities to benefit from the available expertise and skills
- It needs high investment projects and budgets (that are supported by national banks and large investments) to increase crop yield and production to achieve SDGs.
- It needs to follow the agricultural guidelines, and practices for grown crop(s), increase workers skills, and supervision by domain experts.
- It needs high cost to create agriculture and food security infrastructure that utilizes modern technologies and techniques in agricultural and industrial domains
- It needs to determine a fair pricing mechanism for crop(s) / commodities to achieve fair profits for all stakeholders.

5.3Recommendations

The recommendations of study discuss the factors that affected and related with research assumptions and features of FSWD to improve SSW and SRW in Egypt through the following points:

- Reduce APCW, PGR
- Increase WA to be more than 4 million feddans (add new reclaimed areas for WA based on MALR investment projects [40 ,41]
- Cluster the small lands that are cultivated by wheat in sectors (large WA)
- Apply the agriculture rotation (crops cycle)
- Increase the average wheat yield to be 3.5 tons /feddan in agricultural regions. Where the wheat yield from one feedan of clay, valley, or heavy soil = 3.6 – 4.5 tons /feddan, and it yield in desert, outside the valley, or sandy soil =1.8-3.3 tons/feddan [40–43].
- Let one wheat feddan serve from 20 - 40 citizens according to the boundaries of wheat yield production in the previous step.
- Increase the investments, integrated industrial projects in agriculture domains, regions (specially R2, R3, and R4) and use modern agriculture technologies and techniques to reduce crop waste.
- Improved the SRW to 69.6% in 2021, up from 48.2%, with the potential to reach 97% if the research recommendations are applied, as indicated in *Table 18.*

A complete list of abbreviations is summarised in *Appendix I.*

6.Conclusions and perspectives

The IFSMPSSW model was developed to support SSW in Egypt and similar countries. It uses MLC techniques for predicting SSW across Egypt's agricultural regions and governorates. The model architecture identifies wheat production and consumption patterns in Egypt, focusing on factors that affect SSW and the SRW to aid in achieving SDGs. The model predicts SSW for each instance in the dataset, providing decision-makers with insights to manage SRW effectively now and in the future. Utilizing algorithms such as NB, ID3, RF, and RT, IFSMPSSW achieved a prediction accuracy of 92.6%. Its forecasts have improved Egypt's SRW to 69.6%, up from the actual 48.2% in 2021.

Future work includes extending predictions to other essential crops and commodities, aiming to mitigate food supply chain instability and high cereal prices in local and global markets. This will offer decision-makers alternatives to address crop insecurity.

Acknowledgment

Many thanks to the editorial team at IJACR and the reviewers for their insightful comments and support in publishing this research.

Conflicts of interest

The authors have no conflicts of interest to declare.

References

[1] Barakat K. Annual bulletin of the movement production and foreign trade and available for consumption of agricultural commodities in 2021 and other issues. Central Agency for Public Mobilization and Statistics (CAPMAS), CAPMAS, Egypt; 2023.
[2] Resilience B. The State of food security and nutrition in the world. Rome: Building Resilience for Peace and Food Security. 2017:1-132.
[3] https://www.worldbank.org/en/research/commodity-markets. Accessed 29 October. 2023.
[4] Mohamed A, Mohamed M, Kamel A, Al-sayed O, Alawi R. Annual bulletins of foreign trade for agricultural exports and imports in 2021 and previous issues. Economic Affairs Sector (EAS) in Ministry of Agriculture and Land Reclamation (MALR). 2022.
[5] Ali MMR., Hazman M, Khafagy MH, Thabet M, Intelligent decision model to predict and manage the food security status of dry broad beans. International Journal of Innovative Science and Research Technology. 2023; 8(8):2289-99.
[6] Arafa S, Hassan H, Shaltout S, Shaddad H, Zakhary I. A reference study of the repercussions of global crises on agriculture and food: the two cases of the Corona virus (COVID pandemic) and the Russian-Ukrainian war crisis, Economic Affairs Sector (EAS) in Ministry of Agriculture and Land Reclamation (MALR). 2023.
[7] Mamulaidze T. Food security and the importance of big data. International Journal of Innovative Science and Research Technology. 2023; 8(5): 3272-78.

[8] Whittingham KL, Earle AG, Leyva-dela HD, Argiolas A. The impact of the United Nations sustainable development goals on corporate sustainability reporting. BRQ Business Research Quarterly. 2023; 26(1):45-61.

[9] Islam MM. Why nations fail to feed the poor: the politics of food security in Bangladesh. Taylor & Francis; 2022.

[10] Frankenberger TR, Verduijn R. Integrated food security phase classification (IPC). Rome: The Food and Agriculture Organization of the United Nations. 2011:1-90.

[11] Buchanan-smith M, Cocking J, Sharp S. Independent review of the IPC south Sudan. Overseas Development Institute (ODI), London. 2021.

[12] https://www.wfp.org/publications/global-report-food-crises-2023. Accessed 29 October. 2023.

[13] https://www.fao.org/documents/card/en/c/cc0452en. Accessed 29 October. 2023.

[14] Voronenko I, Skrypnyk A, Klymenko N, Zherlitsyn D, Starychenko Y. Food security risk in Ukraine: assessment and forecast. Agricultural and Resource Economics: International Scientific E-Journal. 2020; 6:63-75.

[15] Reda AMM, Hazman M, Khafagy MH, Thabet M. Utilization of data mining classification technique to predict the food security status of wheat. In international conference on soft computing and its engineering applications 2022 (pp. 432-45). Cham: Springer Nature Switzerland.

[16] Brázdil R, Chromá K, Zahradníček P. Demographic yearbooks as a source of weather-related fatalities: the Czech Republic, 1919–2022. Natural Hazards and Earth System Sciences Discussions. 2023; 2023:1-33.

[17] Barakat K(c). Annual bulletin of statistical crop area and plant Production in 2021, and previous issues, Central Agency for Public Mobilization and Statistics (CAPMAS), CAPMAS. 2023.

[18] Salem S. Annual bulletin of the agricultural statistical for agriculture crops in 2021 and other issues, Economic Affairs Sector (EAS) in Ministry of Agriculture and Land Reclamation (MALR), Egypt; 2022.

[19] Wally A, Morgan J, Seifarth K, Egypt: grain and feed annual. United States Department of Agriculture (USDA), 2023.

[20] Abd Eldayem A, Eliw M. Economic analysis of food security of wheat crop in Egypt. New Valley Journal of Agricultural Science. 2022; 2(5):254-69.

[21] Abdalla A, Stellmacher T, Becker M. Trends and prospects of change in wheat self-sufficiency in Egypt. Agriculture. 2022; 13(1):1-12.

[22] Bronson K, Knezevic I. Big data in food and agriculture. Big Data & Society. 2016; 3(1):2053951716648174.

[23] Abdelaal HS, Thilmany D. Grains production prospects and long run food security in Egypt. Sustainability. 2019; 11(16):4457.

[24] FAO O. Meat. OECD-FAO agricultural outlook 2021–2030. 2021:163-77.

[25] Han J, Pei J, Tong H. Data mining: concepts and techniques. Morgan Kaufmann; 2022.

[26] Vipin PN. Introduction to data mining. 2006.

[27] Raja R, Nagwanshi KK, Kumar S, Laxmi KR. Data mining and machine learning applications. John Wiley & Sons; 2022.

[28] Guerlain S, Brown DE, Mastrangelo C. Intelligent decision support systems. In international conference on systems, man and cybernetics. 'cybernetics evolving to systems, humans, organizations, and their complex interactions'. 2000 (pp. 1934-8). IEEE.

[29] Sharda R, Delen D, Turban E. Analytics, data science, & artificial intelligence: systems for decision support. Harlow: Pearson; 2021.

[30] Barakat K. Egypt in figures 2023 and other previous issues, Central Agency for Public Mobilization and Statistics (CAPMAS), CAPMAS, Egypt; 2023.

[31] https://www.capmas.gov.eg/Pages/populationClock.aspx. Accessed 29 Oct. 2023.

[32] Mohamed AM, Al-feel H, Taie S. Food interests analysis (FIA) model to extract the food preferences and interests of Twitter users. Labyrinth: Fayoum Journal of Science and Interdisciplinary Studies. 2023; 1(1):31-48.

[33] Zeng P, Song X, Yang H, Wei N, Du L. Digital soil mapping of soil organic matter with deep learning algorithms. ISPRS International Journal of Geo-Information. 2022; 11(5):1-19.

[34] Spandana K, Swathi R, Yashaswini BV, Vidyashree B, Kumar AH, Recommendation of crop using random forest algorithm. International Journal for Research in Applied Science Engineering Technology. 2021; 9(7): 1834-7.

[35] Dash R, Dash DK, Biswal GC. Classification of crop based on macronutrients and weather data using machine learning techniques. Results in Engineering. 2021; 9:100203.

[36] Kogan F. Global warming crop yield and food security. In remote sensing land surface changes: the 1981-2020 intensive global warming 2023 (pp. 217-75). Cham: Springer International Publishing.

[37] Akhand K, Nizamuddin M, Roytman L. Wheat yield prediction in Bangladesh using artificial neural network and satellite remote sensing data. Global Journal of Science Frontier Research: D Agriculture and Veterinary. 2018; 18(2):1-11.

[38] Vogiety A. Smart agriculture techniques using machine learning. International Journal of Innovative Research in Science, Engineering and Technology. 2020; 9(9): 8061-4.

[39] https://waikato.github.io/weka-wiki/downloading_weka/ , Accessed 29 October 2023.

[40] Nassar S, Zakaria M, Salem S, Musa S, Azouz A, Moslehi N, et al. Updated strategy for sustainable agricultural development in Egypt 2030, Ministry of Agriculture and Land Reclamation (MALR), Egypt; 2020.

[41] https://www.youm7.com/Article/NewsPrint/5797365. Accessed 29 October 2023.

[42] FCRI, Bulletin of technical recommendations for wheat crop growers, Field Crops Research Institute (FCRI), ARC, MALR, Egypt, 2021.
[43] https://www.youm7.com/Article/NewsPrint/5900190. Accessed 29 October 2023.
[44] MSIT, Achievements of the Egyptian Ministry of Supply and Internal Trade (MSIT) in nine years, MSIT, Egypt; 2023.
[45] Sneha N, Gangil T. Analysis of diabetes mellitus for early prediction using optimal features selection. Journal of Big Data. 2019; 6(1):1-9.

Mohamed M. Reda Ali is currently pursuing a Ph.D. degree in Computers and Artificial Intelligence at Fayoum University, Egypt. He serves as an Assistant Researcher at the Climate Change Information Center, Renewable Energy, and Expert Systems within the Agriculture Research Center in Giza, Egypt. His research interests include Intelligent Decision Support Systems, Data Mining, and Expert Systems.
Email: mm3655@fayoum.edu.eg; mreda@arc.sci.eg

Maryam Hazman earned her Ph.D. degree from Cairo University, Cairo, Egypt, in 2009. She is a Computer Science Professor at the Climate Change Information Center, Renewable Energy, and Expert Systems, Agriculture Research Center, Giza, Egypt. Her research interests include Expert Systems, Smart Agriculture, Intelligent Decision Support Systems, Climate Change Information Systems, and Data Mining.
Email: m.hazman@arc.sci.eg

Mohamed H. Khafagy received his Ph.D. degree from Helwan University, Cairo, Egypt, in 2009. He is a Computer Science Professor and the Dean of the Faculty of Computers and Artificial Intelligence at Fayoum University, Fayoum, Egypt. His current research interests include Big Data, Data Mining, and Intelligent Decision Support Systems.
Email: mhk00@fayoum.edu.eg

Mostafa Thabet received his Ph.D. degree from Helwan University, Cairo, Egypt, in 2017. He is an Associate Professor of Information Systems at the Faculty of Computers and Artificial Intelligence, Fayoum University, Fayoum, Egypt. Since 2015, he has been serving as the Director of the Media Center at Fayoum University. His research interests include Intelligent Decision Support Systems, Data Mining, Electronic Commerc, and Stochastic Programming Problems.
Email: mtm00@fayoum.edu.eg

Appendix I

S. No.	Abbreviation	Description
1	AFIS	Acute Food Insecurity Situation
2	AMS	Acute Malnutrition Situation
3	APCW	Average Per Capita of Wheat
4	ARC	Agriculture Research Center
5	AI	Artificial Intelligence
6	ANN	Artificial Neural Network
7	CAPMAS	Central Agency for Public Mobilization and Statistics
8	CFIS	Chronic Food Insecurity Situation
9	CRF	Correlation Ranking Filter
10	CSV	Comma Separated Values
11	DM	Data Mining
12	DMCT	Data Mining Classification Technique
13	DRC	Democratic Republic of the Congo
14	DSQW	Domestic Supply Quantity of Wheat
15	DT	Decision Tree
16	EAS	Economic Affair Sector
17	FAO	Food and Agriculture Organization
18	FBS	Food Balance Sheet
19	FCRI	Field Crops Research Institute
20	FIAM	Food Interest Analysis Model
21	FN	False Negative
22	FP	False Positive
23	FSMW	Food Security Markers of Wheat
24	FSWD	Food Security of Wheat Dataset
25	GFSI	Global Food Security Index
26	GPS	Global Position System
27	ID3	Iterative Dichotomiser 3
28	IDSMPSSW	Intelligent Decision Support Model to Predict the Self-Sufficiency Status of Wheat
29	IFSMPSSW	Intelligent Food Security Model to Predict the Self-Sufficiency Status of Wheat
30	IPC	Integrated food security Phases Classification
31	LR	Logistic Regression
32	MAE	Mean Absolute Error
33	MALR	Ministry of Agriculture and Land Reclamation
34	ML	Machine Learning
35	MLC	Machine learning classification
36	MSIT	Ministry of Supply and Internal Trade
37	NB	Naïve Bayes
38	NDVI	Normalized Difference Vegetation Index
39	PGR	Population Growth Rates
40	Pop.	Population
41	Prod.	Production of Wheat
42	Reg.	Agricultural Region
43	Req. W	Required Wheat
44	RF	Random Forest
45	RMSE	Root Mean Square Error
46	RN	Root Node
47	RT	Random Tree
48	SDGs	Sustainable Development Goals
49	SRSD	Satellite Remote Sensing Data
50	SRW	Self-sufficiency Ratio of Wheat
51	SSW	Self-sufficiency Status of Wheat
52	SVM	Support Vector Machine
53	TCI	Temperature Condition Index
54	TN	True Negative
55	TP	True Positive
56	UN	United Nations
57	USD	United States Dollar
58	VCI	Vegetation Condition Index
59	WA	Wheat Area