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Intelligent Decision Support System for Insects Prediction Framework

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Abstract: Global climate change refers to changes in the long-term weather patterns that characterize the world's regions. The impact of climate change on agriculture is one of the major factors influencing future food security. Changing in temperature leads to outbreaks of pests and diseases thereby reducing plant production. Predicting plant pests and diseases can protect plants from loss by avoiding and controlling the predicted insects and diseases. This research introduces an Intelligent Decision Support System for insects Prediction Framework (IDSSIPF). The proposed model predicts the period in which insects can affect the plant, in addition to alarming farmers about the needed actions to mitigate climate change. IDSSIPF was experimented with to predict the affected insect period in 2019 years. The result of the experiment shows that the prediction started from a real infection period. so decision-makers can use IDSSIPF to mitigate the insects and avoid crop loss and increase productivity. Comparing the prediction results of IDSSIPF with the real periods in 2019, the accuracy of IDSSIPF is 86%.

Keywords: *Intelligent Decision Support System IDSS, Knowledge Base KB, Climate Change Mitigation, Prediction Model*

1. Introduction

Food crops are afflicted by pests and diseases, resulting in major losses for farmers and putting food security in greater danger The discovery of pest insects may result in a loss of productivity if farmers do not respond quickly enough to stop them from spreading [1] Understanding how the weather varies over time and altering management procedures to achieve a better yield challenge to the agricultural sector in Egypt [2]. So, it is important to provide an intelligent system to predict the appearance of a pest in a specific region and alarm the farmer. The study in this paper proposed an intelligent decision framework that, taking into account the weather condition, can daily predict the appearance of insects during a season.

The motivation comes from the need to predict pest insect appearance in a timely manner at many different localities in all Egyptian regions. The prediction is done based on available data that is collected on temperature and relative humidity. The study goal is not to determine the insect population density but to predict (using meteorological parameters) when the first insects would occur in order to provide decision-makers sufficient time to react and reduce the insect population.

IDSSIPF Framework is depending on prediction climate data to calculate the heating unit for each Growth stage lifecycle for plants and insects as a summation of daily Growing degree days(GDD) and Knowledge base for insects, and plants that are determined by domain experts to predict the Insect affection on plants. Experiment for cotton leafworm and study the prediction effect on cotton through 2019 in El-Beheira Gov. and compare results from IDSSIPF with real observation Traps in the same region.

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The sections in this paper are organized as follows: the second section presents the needed terminology. The third section describes the literature review of previous research. The fourth section describes the applied methodology to monitor and predict the development of insects in agricultural production. The fifth section presents a description of the results and a discussion are presented. Finally, the paper ends with concluding.

1.1. Intelligent Decision Support System (IDSS)

An IDSS is an intelligent information system that reduces the time in which decisions are taken in an environmental domain and strengthens the consistency and usefulness of those decisions [3]. IDSS integrates different intelligent techniques in order to create adaptive user interfaces(AUI), such as data mining, artificial neural networks, fuzzy logic, knowledge-based systems, agents, and genetic algorithms [4]. IDSS is an adaptive system that changes its behavior in response to its environment. The adaptive change that takes place is often relevant to achieving objectives or goals.

IDSS was created to assist decision-makers at various stages of the decision-making process by combining modeling tools and human expertise. IDSSs are decision-making aids that are used when there is ambiguity or insufficient information and risk-related choices must be made using human judgment and preferences [5].

1.2. Knowledge base(KB)

A knowledge-based system is composed of two distinct parts: firstly, a knowledge base including an ontology that structures the knowledge from the domain, with a fact base that instantiates the ontology to describe specific situations, and sometimes a rule base that enriches the ontology. Secondly, a reasoning engine is associated with the knowledge representation language but independent of any particular knowledge base.

Precise knowledge of the state of agricultural plots or herds is essential for the farmer, who can now use data collected (images, biophysical measurements, etc.) from connected sensors to obtain more information than can be perceived by the naked eye. with the various digital processes, the farmer can access this information via a dedicated application online or on a smartphone.

1.3. Weather Prediction Model

Weather plays an important role in agricultural production. It has a significant impact on a crop's growth, development, and yields as well as the prevalence of pests and diseases. Meteorologists truly use a mixture of many totally different strategies to come back up with daily weather forecasts, they are [6]: applied mathematics (statistical) prediction, synoptic prediction, Persistence forecast, Computer prediction, and Time Series Analysis.

In [7] Time Series Analysis for Weather Forecasting, predicting certain time series appears to be a severe difficulty in the target area, as current forecasts of specific time series do not purely reflect the capacity to anticipate future actions. Certain time series data cannot be implemented in big datasets, resulting in prediction errors. In [8] It is thought that uncertain time series in weather precipitation forecast might assist to minimize risks and make better everyday judgments. In order to increase the quality of yield in the target region, the determination of anticipating uncertain time series has been identified as a crucial action that must be conducted. As a result, analytical comparisons were carried out in order to establish the yield of forecasting uncertain time series. The restriction resulting from analysis might be utilized as a springboard for new ideas.

Tasks requiring decision-making are limited and rely on human knowledge, experiences, judgments, and preferences. Intelligent Decision System (IDS) technology can be employed in this situation to deliver realistic and consistent choices, as well as to increase the efficiency of decision-making processes. The Intelligent Decision Support System (IDSS) is a component of IDS technology that integrates human knowledge with modeling tools to aid decision-makers in high-level decision-making stages. Data mining (DM) techniques are now commonly used to aid Knowledge Management (KM) tasks, particularly knowledge discovery and knowledge engineering. As a knowledge modeling activity, DM is an emerging data analysis method that is frequently utilized to provide meaningful information for decision-making.

2. Related Work

In [5] Knowledge Discovery Techniques for Talent Forecasting in Human Resource (HR) Application, some of the strategies can be combined with others to achieve improved decision-making outcomes. The power of HR application is the capacity to continually modify and gain new insights, and this might be the HR application of future work. Jantan and his colleagues included KDD approaches with other DSS components in their HR system as in figure 1.

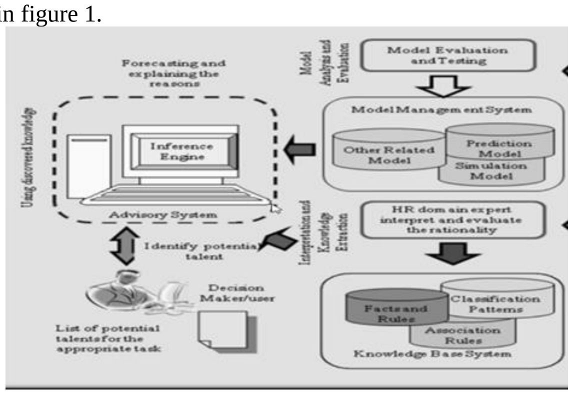

Fig. 1. HR System Architecture [5]

Time Series Forecasting of Temperatures model Autoregressive integrated moving average (ARIMA) has two types: non-seasonal and seasonal that cold SARIMA. It combines them to increase the forecasting accuracy. the SARIMA model may be used to anticipate future values. The variety of parameter combinations used in the grid search in future work. This procedure may aid in identifying models with improved predicting accuracy.

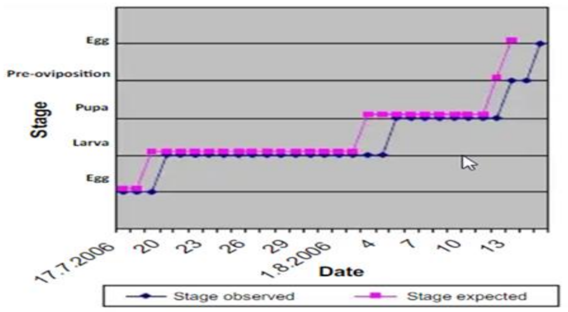

Fig. 2 .Expected stages of S. littoralis in Al-Qalyubiya Gov. [11]

Furthermore, predicting accuracy may be connected not only to SARIMA model parameters but also to the duration of the training set. A follow-up study should look at both hypotheses [9] ARIMA model that predicts the value at the next time step by using data from past time steps as input to a regression equation.

In [10] Forecasts in an autoregressive model correspond to a linear combination of the variable's historical values. In a moving average model, forecasts are a linear mixture of previous forecast mistakes. ARIMA models combine the two methods.

Yones and et. Approved that The easiest technique to anticipate and calculate the average of thermal units in dd's necessary for the completion of S. littoral development is to use daily maximum and minimum air temperatures acquired from satellite photos. The damage caused by pests, particularly the cotton leafworm, S. littoralis, is one of the primary hurdles to the production of additional crops and food for Egypt's rapidly rising population. As a result, a GIS model for computing the degree day's units using remote sensing (RS) and Geographic Information System (GIS) as a platform for cotton pest outbreak prediction is established.

Figure 2 in [11] The average of thermal units in dd's required for the completion of S. littoralis generation development appears to be best predicted and calculated using daily maximum and minimum air temperatures collected from satellite pictures. The average thermal units required for completion of generation are 544.98, 640.63, and 599.66 degrees-days (C^o) as calculated from daily maximum and minimum air temperatures, and the average heat unit are 50, 400, 490, 520 for growth stage egg, Larvae, pupa, and adults.

3. Methodology

The Intelligent Decision Support System for insects Prediction framework (IDSSIPF) is an extension of our previews model Intelligent Decisions for Climate Change Mitigation Model (IDCCM) [3]. According to the expert's consideration from the Intelligent Decisions for Climate Change Mitigation Model (IDCCM) offers relevant information (flexible, complete, accurate, and timely) as in figure 3. The introduced methodology also aids in improving Egypt's food yield and quality through sound agricultural practices and climate-smart agriculture. To address the knowledge gap between the climate prediction model

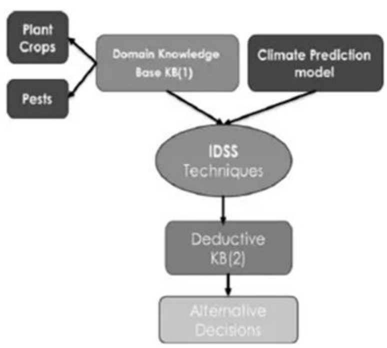

Fig. 3. IDCCM Model [3]

and the knowledge base of domain researchers to forecast intelligent decisions based on a set of theoretical principles that explain the "rationality" on time, KB to support the automatic judgments using a selected intelligent decision support system IDSS methodologies that fit with the dataset to the deductive second level of knowledge base [3].

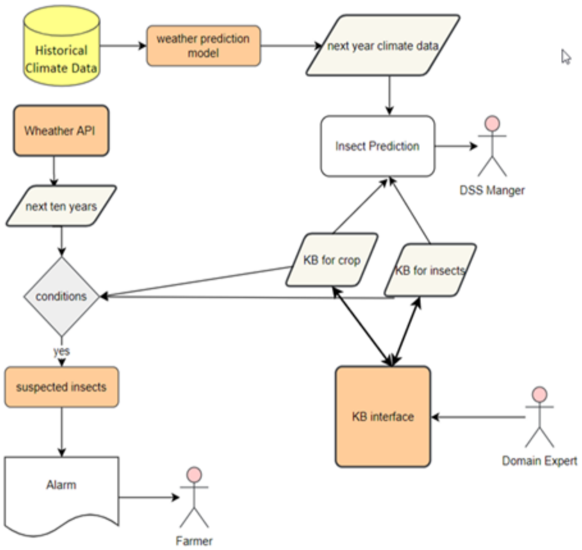

Fig. 4. IDSSIPF Model Structure

Figure 4 shows, that in order to predict insects which is respond to climate change, we require in-depth knowledge of the knowledge base components relevant to predicting a particular system., The highly diverse microclimates are produced by interactions between insects and biotic environments like plants. Host plant physiology frequently controls these microclimates. as well as weather conditions. An Intelligent Decision Support System for insects Prediction framework (IDSSIPF) includes Historical data, the Knowledge base for insects, the Knowledge base for plants, Insect prediction, and Weather API. these components will be illustrated in the following sub/sections. There are three users Decision Support Manager, Domain Expert, and the end user Farmer. The input to the model are historical climate date for a certain location and knowledge base from domain experts for insects and plants as heat unit for each stage, and output for decision makers can predict certain insects will affect the plant in any region in light of the predicting climate data for these regions, on the other hand, provide farmers by the predict of their growing plants is affected through 5-10 days by insects or not, depends on forecasting weather also provide information if the plants will be affected how to avoid and decrease their effects on plant production.

3.1. Historical Data

Historical data includes a dataset that is collected for actual climate data monitored from meteorological stations in Egypt. the dataset contains the attributes: maximum and minimum temperature, average temperature, wind speed, relative humidity, and the number of hours of sunshine. Weather data for ten years (2009-2019) is collected from the Egypt Meteorological department depending on GIS locations.

In [3] Meteorologists truly use a mixture of many totally different strategies to come back up with daily weather forecasts, they are applied mathematics(statistical) prediction, synoptic prediction, Persistence forecast, Computer prediction, and Time Series Analysis. Time Series is an ordered collection of values of a quantity obtained over a specific period or since a certain point in time as observations that are recorded in successive and equidistant time steps. time-series depends only on the historical development of the data and not on other effects. Time Series Forecasting of Temperatures model Autoregressive integrated moving average (*ARIMA*) has two types: non-seasonal and seasonal that cold *SARIMA*. It combines them to increase the forecasting accuracy. the *SARIMA* model may be used to anticipate future values. The variety of parameter combinations used in the grid search in future work.

Time series ARIMA (p, d, q) model use (1) is mainly used to project future values using historical time series data [10].

$$y_t = c + \sum_{i=1}^{p} \varphi_i\, x_{t-i} + \sum_{j=1}^{q} \theta_j\, \varepsilon_{t-j} \qquad (1)$$

Where: y_t – is a stationary stochastic process,

c –is the constant,

ε_t – is the random error or white noise disturbance term,

p – auto-regressive (AR) models,

φ_i – means AR coefficient,

$\emptyset_j$ – is the moving average coefficient,

x_t–is the value that is observed at t and q are moving-average terms.

in order to predict the daily climate data, the seasonal *ARIMA* (p, d, q) (*P*, *D*, *Q*) m is used as *SARIMA* (p, d, q) (*P*, *D*, *Q*) m. the following (2) to predict the daily data.

$$y_t = \frac{c + \theta(\beta^m)\theta(\beta)\varepsilon_t}{\varphi(\beta^m)\varphi(\beta)(1-\beta^m)^D(1-\beta)^d} \qquad (2)$$

where: β – is applied to time series x_t characterized by time interval t,

m– is the seasonal period,

$\varphi(z)$ and $\theta(z)$ – are polynomials of orders P and Q, respectively.

Each polynomial contains no roots inside the unit circle. If c ≠ 0, the forecast function is an implied polynomial of order *d* + *D*. *SARIMA* forecasting task needs to calculate the mean absolute error (*MAE*) as in (3), the root mean squared error (*RMSE*) as in (4), and the mean absolute scaled error (*MASE*).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_t| \qquad (3)$$

where: $|e_t|$ – is an absolute error at time t.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_t^2} = \frac{MAE}{Q} \qquad (4)$$

Seasonal naive forecasts are used for more accuracy in climate data prediction. In (5) is used to predict the climate data in the presented work.

$$Q = \frac{1}{N-M}\sum_{j=m+1}^{n} |y_j - y_{j-m}| \qquad (5)$$

The Prediction model is depending on historical data on climate change and GIS location. knowledge modeling component as a knowledge for the decision-making process is divided into two sections knowledge for insects, and knowledge for plants that can be manipulated by Domain Expert through knowledge interface.

3.2. Knowledge Base for Insects

The domain expert uses the KB interface in order to acquire the needed insect knowledge bases. The collected knowledge is organized in an ontology. Ontologies are a component of computer systems that help users accomplish a task. This assistance can take many forms, from automating a prediction decision to finding information to help make a decision. Knowledge can also be generated by the analyses of target information. In this case, the difficulty lies in presenting these analyses to human actors in the most intelligible way [12].

The insect knowledge base includes the required environment for insect generation. The insect life cycle is divided into stages. The duration from one stage in the life cycle to the same stage in the progeny is referred to as a generation. Temperature and food availability are two important environmental elements that may impact generation time. Temperature increases between the top and lower limits may hasten insect growth, reproduction, and survival [13]. Life stages of insects differ in ability to move, and thus exposure to microclimate variability. The survival of without moving life stages, such as eggs, pupae, Larval, and adults is closely tied to their environment, the identification of pests that infect various cultivated crops is of great importance, as these pests vary according to the variety of crops. For example, Cotton leaf worm (littorals Spodoptera) KB is selected to be acquired as it is considered one of the most dangerous pests of the order Lepidoptera, family Noctuidae that attacks many crops, and vegetables. The cotton leaf worm is native to Africa and the Middle East, which is a real problem, especially for vegetables, ornamentals, and forage legumes in the Mediterranean basin and for the cotton crop in Egypt [14].

```
<? xml version="1.0" encoding="utf-8" ?>
<Insects>
 <!--No_Generation:الحشرة اجيال-->
 <Insect Id="1" Name="cotton leaf worm" TypeId="1" ImagURL="" No_Generation="1"
Starting_Date="01/03">
   <condition UpperTempratur="35" LowerTempratur="18" BaseTempratur="9.98"
GenConvergDegree="550"></condition>
   <Generation id="1" GNo="1”>   <GrowthStages>
    <!--GDD:Growing degree days -->
    <GrowthStage id="1" HU ="50" Gname="Eggs" mageURl=""></GrowthStage>
    <GrowthStage id="2" HU ="330" Gname="Larvae" imageURl=""></GrowthStage>
    <GrowthStage id="3" HU ="520" Gname="Pupae" imageURl=""></GrowthStage>
    <GrowthStage id="4" HU ="550" Gname="Adult" imageURl=""></GrowthStage>
   </GrowthStages>
    <Host_Plant  >
     <!--العائل-->
     <plant id="1" HostId="1" name="alfaalfa" I_growthstage="Larvae" P_growthstage="">
</plant><!--البرسيم-->
    </Host_Plant>
   </Generation>
   <Generation id="2" GNo="2"><!-- -->
    <GrowthStages>
     <!--GDD:Growing degree days -->
     <GrowthStage id="1" HU="50" Gname="Eggs" imageURl=""></GrowthStage>
```

Fig. 5. Knowledge base of Insects

Figure 5 shows the KB of insects. It contains the types of insects and their names, the surrounding environment, the different stages of the insect, the needs for hours of heat acquired in each stage and the phase that causes damage to the plant, and the appropriate temperatures for the growth of the insect and the number of generations.

3.3. Knowledge base for plants

KB of Plants contains the knowledge of the plant in terms of planting date period, plant type, growth stages, crop's base temperature, heat unit HU, GDD for each stage, and the upper and lower temperature that caused stress on the plant without affecting the roots, natural growth and productivity. All knowledge of plants is set and revised periodically by domain experts. As it is changed according to the crop varieties which are being developed in Egypt. Rising temperature increases the process of photosynthesis, transpiration, and respiration, and affects the stages of plant growth through the transition from the vegetative stage to the flowering stage[15]. Low temperature disturbs physiological processes such as water system, mineral nutrition, photosynthesis, respiration, and metabolism within the plant [16]as shown in figure 6.

```
<?xml version="1.0" encoding="utf-8" ?>
<crops Ccount="">
<crop id="1" plantation_date="1/4" name="cotton" image="" location="" UpperTempratur="43"
LowerTempratur="15" BaseTempratur="10.14"><!--16.6-->
   <growth_Stages TotalNo="8" >
    <!--GDD:Growing degree days -->
<growth_stage id="1" name="Planting" HU="60" no_dayes=""></growth_stage><!--4 to 9 day-->
  <growth_stage id="2" name="Emergence" HU="535" no_dayes=""></growth_stage><!--475--><!--
27 to 38>
    <growth_stage id="3" name="First Square" HU="700" no_dayes=""></growth_stage>
    <growth_stage id="4" name="Flower" HU="850" no_dayes=""></growth_stage><!--775--> <!--45
to 65-->
    <growth_stage id="5" name="Open Boll" HU="1820" no_dayes=""></growth_stage><!--45 to 65--
>
    <growth_stage id="6" name="Maturity" HU="2500" no_dayes=""></growth_stage>
    <growth_stage id="7" name="Picking" HU="3500" no_dayes=""></growth_stage
```

Fig.6. Knowledge base of plants

3.4. Insect prediction

Insect prediction depends on the weather and its hosted plant parameters. Insects need GDD to develop as well as feed for their plant host. So the input to this component is the insect kb, plant kb (which are extracted from domain experts using the knowledge base interface), and the next year's climate data (which is predicted from the weather prediction model).

3.5. Growing degree days (GDD)

One of the most important indications in understanding plant phenology is Growing Degree Day (*GDD*), also known as heat units (HUs) or thermal time concept [17]. *GDDs* are a phonological and climatic measurement that represents the differential in temperature change in the crop as in (6) to calculate *GDD* from minimum, maximum, and base temperature. To grow a high-yielding, high-quality crop, follow these steps for the Cotton plant [18].

$$GDD = \mathrm{Max}\left[0, \left(\frac{(\mathrm{T_{MAX}} - \mathrm{T_{MIN}})}{2} - \mathrm{T_b}\right)\right] \qquad (6)$$

where: T_b– crop's base temperature is determined by a domain expert, T_{MAX} and $\mathrm{T_{MIN}}$ – the maximum and minimum daily air temperatures that must satisfy these conditions

$$T_{MAX} = \begin{cases} \mathrm{T_{MAX}} & 37.7\ ℃ > \mathrm{T_{MAX}} > \mathrm{T_b} \\ 37.7\ ℃ & \mathrm{T_{MAX}} \geq 37.7\ ℃ \\ \mathrm{T_b} & \mathrm{T_{MAX}} \leq \mathrm{T_b} \end{cases} \qquad (7)$$

$$T_{MIN} = \begin{cases} \mathrm{T_{MIN}} & 37.7\ ℃ > \mathrm{T_{MIN}} > \mathrm{T_b} \\ 37.7\ ℃ & \mathrm{T_{MIN}} \geq 37.7\ ℃ \\ \mathrm{T_b} & \mathrm{T_{MIN}} \leq \mathrm{T_b} \end{cases} \qquad (8)$$

where: 37.7 ℃– the upper edge temperature that plant roots have trouble in absorbing water for growth and development.

In (9) is presented the calculation of heat units *HU* depending on summation of daily *GDD*.

$$HU = \sum_{i=1}^{n} \mathrm{GDD_i} \qquad (9)$$

For determining insect growth stages, the needed *GDD* is calculated according to algorithm as in figure 11. That the first date insect development is determined for each growth stage for each insect generation. As the domain expert opinion, the insect feed from its hosted plant. The insect can feed from specific plant growth stages, and not all growth stage.

```
Input    C a set of all crop                    output:
     GDD is growing degree days        list of effected crop and non-effected
        I is an insect class
        R is region name
        W a set of all prediction weather for certain region
        IG is a set of all insect generations
        IGGS is a set of all Growth stages of certain generation
        CGS is a set of all Growth stages of certain crop
        Hu is heat unit
Steps
1-predictInsectG= Insect_Prediction (I, W, IG, IGGS)
2- PredictCrops= Crop_Prediction(I, W, C)
3-Procedure Match(predictInsectG, PredictCrops)
  For each insectgen  in predictInsectG do
    Ggrowthstage= insectgen.gs_name,   Ggsdate= insectgen. startdate
     For each crop  in PredictCrops do
          Cgs= crop. gs_name,   Cgsdate=crop.stratdate
          Diff=mod(Ggsdate- Cgsdate)
          Switch Diff:
          Case 0: effect=100%
          Case <5: effect=75%
          Case <10: effect=50%
         Default: effect= noeffect
     End for
End for
Return results
End Procedure
```

Fig. 7. Algorithm of prediction model

So, as in figure 8 plant growth stages were predicted using the GDD which tacking in consecration the plant plantation date and heat unit HU. This knowledge is different from one crop variety to another. so, crop KB is needed to be changed periodically depending on new varieties that developed to migrate to climate change. After determining the insect and its host growth stages, the model will predict the periods in which the insect will affect its host plant. The used algorithm to predict these periods is shown in figure 7. Prediction for plant growth stages measured by GDD which tacking in consecration the plant plantation date and heat unit HU that entered by domain Expert and change periodically depends on climate change. after determining the insect and its host growth stages, the model can predict if the insect will effect on plant or not by a match for each insect is affected a plant in a certain growth stage and the effecting on the plant also on a certain growth stage or period of time that determined by a domain expert in a knowledge base of inset and plant.

```
Procedure Insect_Prediction (I, W, IG, IGGS)
    IGGS  ←  empty set
    Results ← empty set
     For each g in IG do
       IGGS=getGrowthstages(g, I)
          For each gs in IGGS do
              For each day in W do
                ggd=(day.MaxTemp+day.MinumTemp)/I.Basetemp
                hu=sum(ggd)
                difference=hu-gs.hu
                if difference<10
                  update(gs.name,gs. calculted_hu, gs.noOf_dayes, startdate)
                else
                  Results.add(gs)
                End for//day
          End for//gs
     End for//IG
Return Results
End Procedure
```

Fig.8. Crop Prediction Algorithm

3.6. Weather API

API weather forecasts differ from climate predictions, Weather forecasts have a time horizon of about the next 10 days, while climate models depend on the prediction of insect effects for the future long period increasing more than a year. The physics of climate modeling is similar to weather forecasting, but Weather forecasts are different regarding daily maximum and minimum temperatures, rain quantity may fall, and how fast the wind will

```
Procedure Crop_Prediction (I, W, C)
CGS  ← empty set
 Results  ← empty set
     For each p in C do
       CGS=getGrowthstage(p)
         For each gs in  CGS do
           For each day in W do
               ggd=(day.MaxTemp+day.MinumTemp)/2- p.Basetemp
               hu=sum(ggd)
               difference=hu-gs.hu
               if difference<10
                 update(gs.name,gs. calculted_hu, gs. noOf_dayes, startdate)
               else
                 Results.add(gs)
             End for//day
           End for//gs
       End for//C
Return Results
End Procedure
```

Fig. 9. Crop Prediction Algorithm

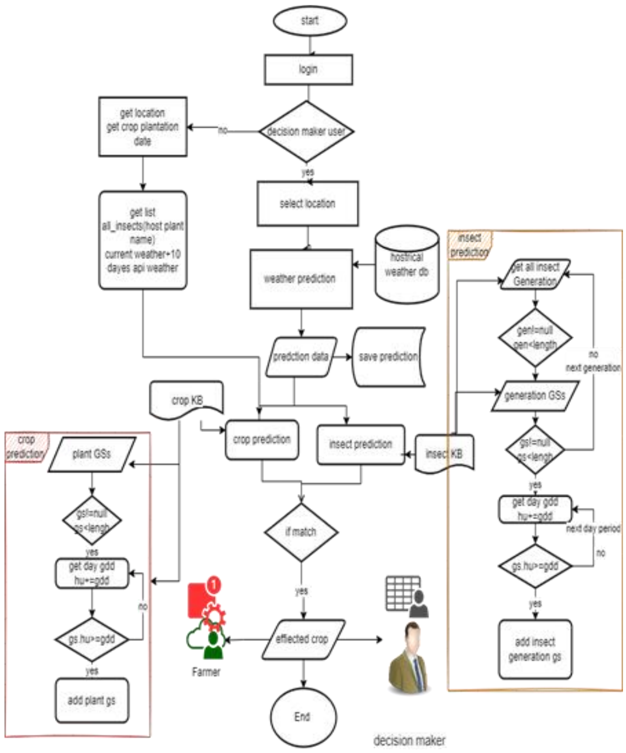

Fig. 10. IDSSIPF Flow Chart

blow in a specific region and time. API weather presents information and alerts to the end user for the shortest time relying on more accurate data predicting getting. This information presents solutions to control his farm from the possibility of infestation by insects before it occurs in an appropriate period to take due precautions and maintain production as much as possible.

4. Experimental

Using the IDSSIPF to predict periods that the insect affected the selected plant. In Figure 10, the used scenario in our experiment. The following steps are following:

- Select a location and number of used years (2009 -2018) to collect historical climate data for predicting two years' climate.
- Using time series seasonal model *SARIMA* to predict especially Naïve model climate data using the selected location and collected data for predicting climate data in season 2019 years daily. Naïve model is used because it provides more accurate predicting data nearest to real weather data.
- Using knowledge base of insects and plants that was revised by domain experts and predicted climate data to calculate the Growing Degree Day *GDD* for the growth stage in each generation of insect depends on the start date of generation from insect *KB* and accumulated *GDD*. The domain expert enters the insect kb for cotton leafworm and plant kb for cotton.
- Obtaining the Heat Unit HU for each cotton growth stage, then using an algorithm in figure 9 to determine if insects will effect on plant or not. The result is shown in figure 11 which presented 5 periods (4th week of May, 3rd week of June, 3rd week of July,2nd week of August, and 2nd week of September) in which cotton plant lifecycle can be affected by cotton leafworms larvae GS.
- In the first and last periods of the 5 periods, their effects are limited or no effect because in the first period the plant is in the germination stage, and in the last, the plant is in the

Table 1. Comparing between IDSSIPF results and real observation Traps of Cotton Leafworm in El-Beheira Gov. 2019 [19]

Month	May				June					July				August					September			
Weak day	4	11	18	25	1	8	15	22	29	6	13	20	27	3	10	17	24	31	7	14	21	28
Real observation	-	-	9	11	15	32	41	68	351	89	247	40	310	87	64	88	45	74	28	30	44	24
Real Degree	0	0	N	N	N	N	N	M	H	M	H	N	H	M	M	M	M	M	N	N	N	N
IDSSIPF	N	N	N	H	H	M	N	M	H	H	N	N	H	N	N	M	H	N	N	H	H	N

harvest stage.

In order to evaluate IDSSIPF, we compared its result with the real affected of cotton leaf worm insect percentages on the cotton crop in 2019 [19]. They collected the number of insects on the plant by using the Pheromone Traps to Monitor Population Fluctuations. In their work, they did not care if the insect affects the plant or not.

In IDSSIPF, the affected on the plant is predicted. That will lead to the non-excessive use of pesticides, which is one of the goals of agricultural sustainability through accurate targeting and future identification of plant infestation.

Comparing *IDSSIPF's* result with the real affected period during the summer season of 2019. on the fields of cotton crops. Table 1 displays the comparison between *IDSSIPF's* result and the real population of Cotton leafworms in El-Beheira Gov. during the summer season 2019 on the fields of cotton crops. The observed real Number of insects are classified into: -

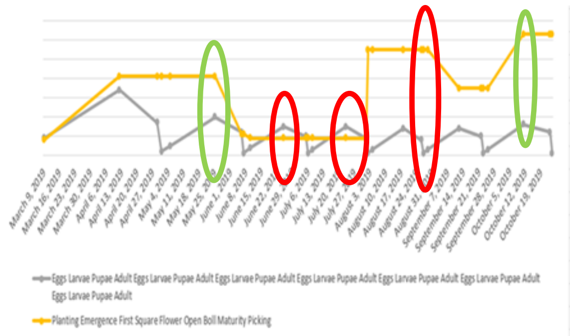

Fig. 11. Predicting GS of Cotton and leafworm in Behara Gov. 2019 from framework

- None (non) no effect
- Normal (N) if a number of insects <50
- Mid (mid) effect if a number of insects>50 and <100
- High(H) effects. if a number of insects>100.

IDSSIPF 's result can classify result degree to high(H) the occurred damage to the plant occurs when the growth stage of the insect (larva) falls with the growth stage of the plant (Emergence, First Square, Flower, Open Boll), else results from degree is Normal(N). Figures 11 and Table 1, in the 2019 season in real the average number of months was 103.40, at Sharnub village [19].

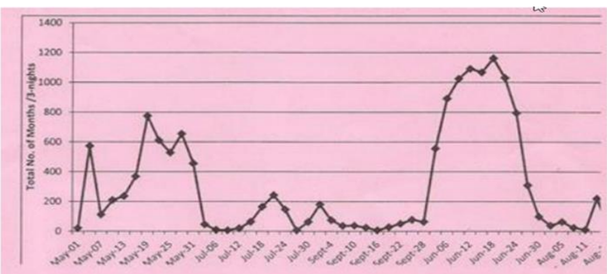

Fig.12. Deviation between observed and expected annual generation of S. Littoralis in Kafr-ElShiekh region during season [21]

Also, the number of the generation of cotton leafworm was compared with the result in [20]. The generation of cotton leafworm on the cotton plant has 3 generations 10/6, 8/7, 4/8 from IDSSIPF for Kafr El–Sheikh region that nearly matched the real data observed in the same region that the 3 generations on 21/6,18/7, and 14/8 as shown in figure 12 due to the climate change.

To evaluate the performance of the proposed framework using the data in Table 1, the performance metrics of the models can be calculated [21]. There are four different values obtained from the models on the confusion matrix as shown in figure 12. These values are TP, TN, FP, and FN [22]. In the study, these values are expressed as follows.

- **TP**: Predict true Actually true as Classification of high effect
- **TN**: Predict false Actually false as Classification of normal or no effect
- **FP**: Predict true Actually False Classification of prediction with information of domain expert suggested effect
- **FN**: Predict false Actually True Classification

		Predicted		
		0	1	∑
Actual	0	10	1	11
	1	2	8	10
	∑	12	9	

Fig. 12. Confusion matrix of IDSSIPF

Performance metrics are used to evaluate and compare the performance of IDSSIPFs. Accuracy, precision, recall, and F-1 Score metrics were used in the study. The formulas of these metrics are shown in Table 2.

Table 2. Performance metrics formulas

Recall(R)	$R = \frac{TP}{TP+FN}$	0.80
Precisions(p)	$P = \frac{TP}{TP+FP}$	0.86
F-score(FS)	$FS = 2 * \frac{P*R}{P+R}$	0.83
Accuracy(A)	$A = \frac{TP+TN}{TP+FP+TN+FN}$	0.86

Accuracy is best used if the most number of predictions match the actual values across balanced classes. Precision is best used if predictions are correct. The recall is best used when maximizing the correctly predict positives. Finally, F-Score is a combination of precision and recall. It is used when predictions while maximizing the number of correctly predicted positives.

IDSSIPF can predict 80% from the real affected period (recall), and the real affected period from the predicted periods is 86% (precisions). The accuracy of IDSSIPF is 86%.

5. Conclusion

Given the changes in the climate in Egypt in the recent period and the impact of this on the spread of many diseases and insects on plants and consequently the lack of expected production as well as the impact on the germination rate and planting seasons in plants. Many software programs have also been developed in the plant sector to help farmers plan and manage crop fertilization, pest control, or irrigation. Nowadays, with the upsurge in digital technology, a new generation of *DSS*. Intelligent Decisions for Climate Change Mitigation framework *IDSSIPF* provides a solution for decision-makers in the long run to know the extent of the impact of these insects in the future and take the necessary measures to maintain productivity, by predicting climate data and the generations of different insects, as well as predicting the stages of plant growth and the extent of the impact of insects on the plant in the long run. The model also provides a suggested immediate solution to the farmer by warning and alarm of the possibility of a certain insect infestation at a certain period of time and providing preventive and treatment measures to maintain production. *IDSSIPF* provides for the non-excessive use of pesticides, which is one of the goals of agricultural sustainability through accurate targeting and future identification of plant infestation.
In the future, we plan to extend the crop kb and insect kb by adding more insects and crops. Also, we intend to enhance the 10-day alarm part. An early warning knowledge base will be added to provide farmers with alarms about all operations needed to mitigate climate change.

Author contributions

Ayman Mohamed: Conceptualization, Methodology, Software, Field study **Maryam Hazman**: Data curation, Writing-Original draft preparation, Software, Validation., Field study **Sayed AbdelGaber, Mona Nasr**: Visualization, Investigation, Writing, Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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