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A Low Cost Early Warning System for the protection of Wheat against Brown Rust

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Abstract: **This paper proposes a low cost early warning system for the protection of wheat crop against the various diseases that are developed through pests and pathogens on the crop. A field monitoring device that will collect environmental parameters and the collected data will be processed to find out the severity of infection that has occurred on crop. Through this system farmers can get the information about the severity rate of crop infection on their cell phones. Timely warning of the plant diseases can protect the crop from pesticides infection. Weather sensors like temperature, humidity, leaf wetness, and solar radiation are interfaced through ARM-32bit LPC2129 microcontroller. Whole system is used to collect the environment parameters. These collected environment parameters are processed to forecast the likeliness of disease to infect the crops. The disease forecasting can protect the crop from damaging at very early stage and this also saves the amount of pesticides used.**

Keywords: **Early warning system, ARM-32-bit microcontroller, LPC2129, Beta regression model.**

1. INTRODUCTION

The prime objective of present project is designing a low cost early warning system that would provide end users an early warning in case of plant diseases, automated storages solutions, seed quality assessment and protection. It is very important to identify plant diseases before it affect the crops. For this an early warning system has to be developed which would be based upon the continuous monitoring of certain parameters, the degradation of which result in lack of proper growth or diseases in plants. The parameters include air temperature, relative humidity, leaf wetness, wind speed, rainfall, soil moisture, ground temperature and solar radiation.

Occurrence of pests depends on these environmental parameters. They play an important role in the formation of a layer of pesticides on the leaves of plant. Therefore the environmental parameters collected are processed using beta regression model and the severity index of crop infection is calculated. Beta regression is a forecasting model. Based on the severity index alert is sent to the farmers. The previous data responsible for brown rust helps in forecasting the next occurrences of disease.

2. PROPOSED WORK

The system was divided into three different phases of operation

1. Field data acquisition.
2. Data Processing
3. Forecasting of disease.

Field data acquisition.

1. To make the system low cost and effective we have used ARM -32 bit micro-controller i.e. LPC2129.
2. To obtain weather parameters we have interfaced different field sensors like temperature sensor, RH sensor, leaf wetness sensor, etc.
3. The parameters recorded by field sensors are stored in a database using RS-232 field communication.
4. The collected data is processed and the coefficients of beta model are calculated.

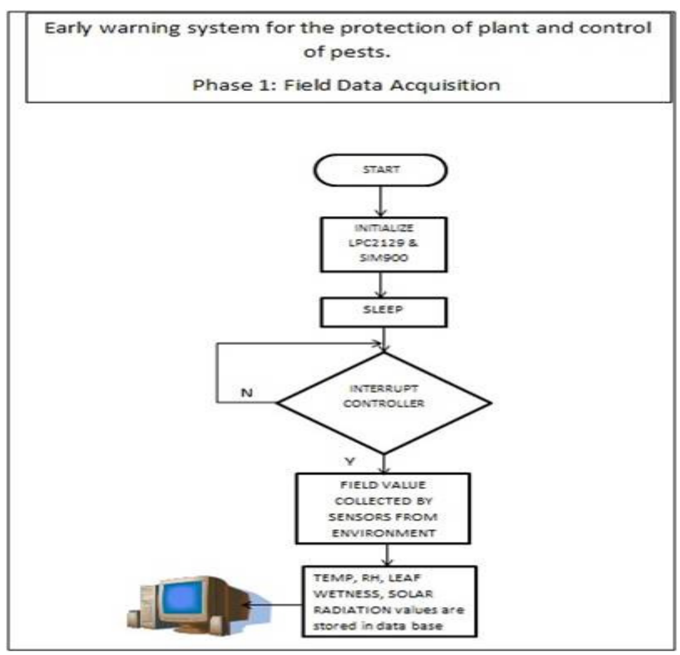

Fig. 1: field data acquisition. Block diagram

Data Processing

1. Data collected is transferred through serial to parallel communication to the control station. Control station consists of a laptop or personal computer.
2. Data received is saved into an excel sheet.
3. Coefficients of Beta model is calculated using Microsoft excel.
4. The coefficients are used to calculate the severity index of the disease to appear.

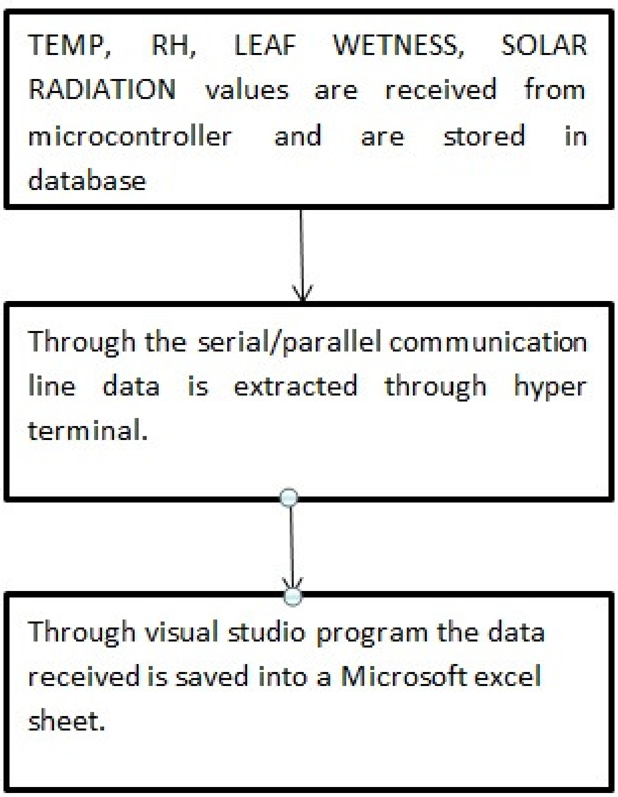

Fig 2: Data Processing Block Diagram

Disease forecasting.

1. When the severity index is calculated the likeliness of disease to appear on crop will be forecasted to the farmers.
2. The forecasting will be done through GSM based mobile communication. For this communication purpose we interfaced SIM900 GSM module with the microcontroller.
3. Through GSM based communication we can send alert message to the farmers.
4. An alert message is in the form of NO RISK, LOW RISK and HIGH RISK.
5. For further future reference all the data will be updated over a server which can be accessed over internet.

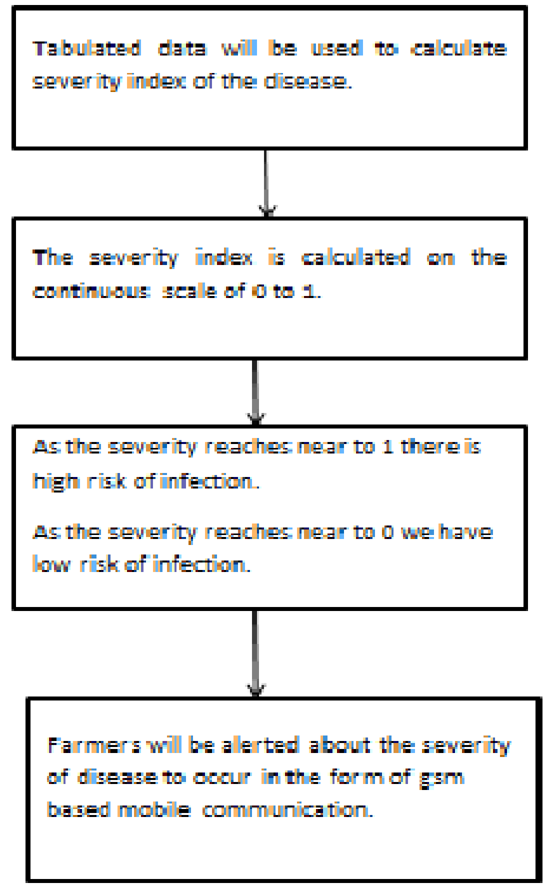

Fig 3: Disease Forecasting Block Diagram

3. Hardware Description

ARM7TDMI-S PROCESSOR

The ARM7TDMI-S is a general purpose 32-bit microprocessor. It offers high performance and very low power consumption.

The ARM architecture is based on Reduced Instruction Set Computer (RISC) principles, and the instruction set are much simpler than those Complex Instruction Set Computers. This simplicity results in a high instruction throughput and impressive real-time interrupt response from a small and cost-effective processor core.

Pipeline techniques are employed so that all parts of the processing and memory systems can operate continuously.

The ARM7TDMI-S processor also employs a unique architectural strategy known as THUMB.

The key idea behind THUMB is that of a super-reduced instruction set.

Essentially, the ARM7TDMI-S processor has two instruction sets:

- The standard 32-bit ARM instruction set.
- A 16-bit THUMB instruction set.

THUMB code is able to provide up to 65% of the code size of ARM, and 160% of the performance of an equivalent ARM processor connected to a 16-bit memory system.

SENSORS:

Relative Humidity / Temperature Probe:

The Model 41382VC Relative Humidity/Temperature Probe combines high accuracy humidity and temperature sensors in a single probe. The output signal is 0-1 V (standard) or 0-5 V (user-selected option) for both relative humidity and temperature. RH range is 0-100%. Temperature range is -50 to +50°C.

Leaf Wetness Sensor (MODEL LWS 40020):

The Dielectric Leaf Surface Wetness Sensor (LWS) is an innovative new sensor that accurately and affordably measures the duration of leaf-surface wetness. The LWS measures leaf surface wetness by measuring the dielectric constant of the sensor's upper surface approximately 1 cm from the upper surface of the sensor. The dielectric constant of water (80) and ice (5) are much higher than that of air (1), so the measured dielectric constant is strongly dependent on the presence of moisture or frost on the sensor surfaces. The sensor outputs an mV signal proportional to the dielectric of the measurement zone, and therefore proportional to the amount of water or ice on the sensor surface

Wind Monitor (MODEL 05103V):

The wind speed sensor is a four blade helicoids propeller. Propeller rotation produces an AC sine wave voltage signal with frequency directly proportional to wind speed. Slip rings and brushes are eliminated for increased reliability. The wind direction sensor is a rugged yet lightweight vane with a sufficiently low aspect ratio to assure good fidelity in fluctuating wind conditions. Vane angle is sensed by a precision potentiometer housed in a sealed chamber. With a known excitation voltage applied to the potentiometer, the output voltage is directly proportional to vane angle. A mounting orientation ring assures correct realignment of the wind direction reference when the instrument is removed for maintenance.

Total Solar Radiation (MODEL PYR):

This is a pyrometer type sensors used to measure broadband solar irradiance on a planar surface and is a sensor that is designed to measure the solar radiation flux density (in watts per meter square) from a field of view of 180 degrees. It is developed by Decagon devices, USA.

Precipitation Gauges (MODEL P/N 100508):

The accurate measurement of rain and snow precipitation remains one of the most basic elements of hydrological and meteorology studies. The P/N 100508 series of precipitation gauges with a six (6) inch funnel diameter has been designed to measure rainfall and precipitation in remote and unattended locations. These gauges are high quality instruments that provide precise measurements with long term performance. The tipping bucket design allows accurate repeatable measurements, requires no regular operator maintenance, and is economical and proven in operation. All components of the P/N 100508 series rain gauges reflect the environmental requirements of a continuous duty instrument.

4. SOFTWARE IMPLEMENTATION

In this project software for our early warning system was developed using KEIL, MATLAB and LABVIEW. The hardware interfacing part was performed using KEIL software and the coefficients for our equation are calculated by MATLAB code. The front panel or the GUI of the system to monitor changes in parameter is designed using LABVIEW.

Software Development using KEIL:

- Different analog sensors used in this project are interfaced to LPC2129 ARM -7 TDMI micro controller.
- Each sensor is connected and interfaced through inbuilt 10 bit 8 channel ADC.
- Value obtained from sensor is send to PC through RS-232 DB9 connector.
- After the parameter estimation and the calculation of severity index the value is sent to controller for forecasting.
- The output is shown on the LCD panel and through GSM based communication using SIM 900 risk level is sent to farmers in form of message.

Software Development using LABVIEW:

For the interfacing of hardware and sensors and for acquiring signal in particular format for required output as per need of this application, graphical programming was done in the

LabVIEW. Different type of VI (VI is graphical programming window in LabVIEW) were made for different purpose as per need of the project in scan interface mode of LabVIEW.

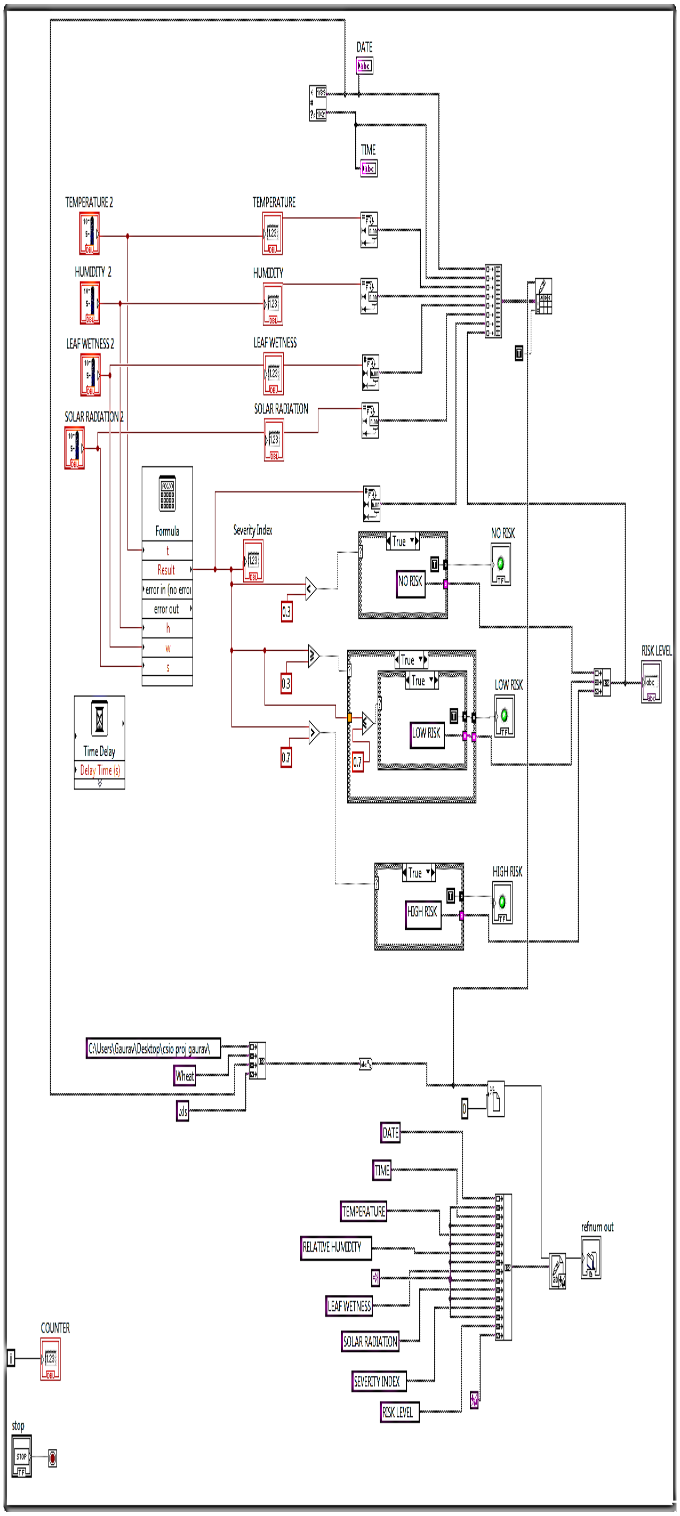

Fig 4: Block Diagram of Brown Rust.VI

Software Development using MATLAB:

Using MATLAB the one's coefficient of equation is derived to generate the equation for wheat rust using logistic regression model.

Logistic regression model:

In statistics, logistic regression or logit regression is a type of regression analysis used for predicting the outcome of a categorical dependent variable (a dependent variable that can take on a limited number of values, whose magnitudes are not meaningful but whose ordering of magnitudes may or may not be meaningful) based on one or more predictor variables. That is, it is used in estimating empirical values of the parameters in a qualitative. The probabilities describing the possible outcomes of a single trial are modelled, as a function of the explanatory (predictor) variables, using a logistic function. Frequently (and subsequently in this article) "logistic regression" is used to refer specifically to the problem in which the dependent variable is binary—that is, the number of available categories is two—and problems with more than two categories are referred to as multinomial logistic regression or, if the multiple categories are ordered, as ordered logistic regression.

5. RESULT AND ANALYSIS

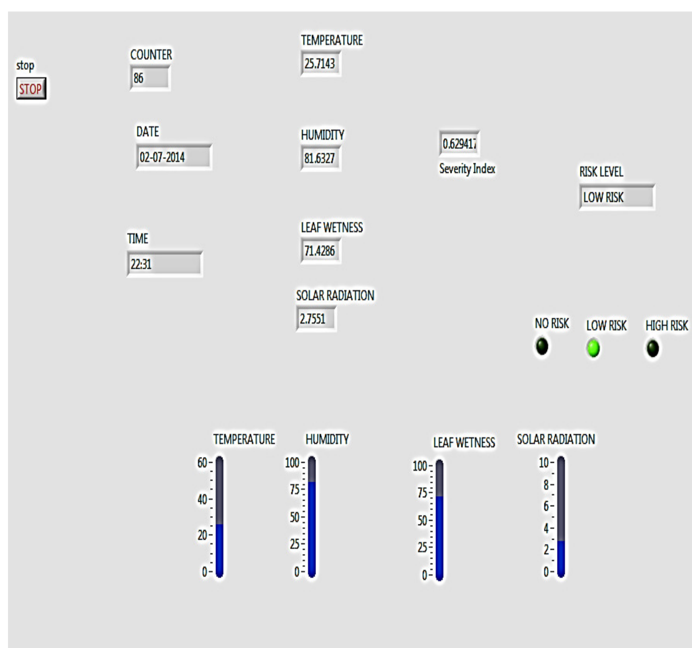

Fig 5: Front Panel of Brown Rust.Vi

- Varying Temp, Humidity, Leaf Wetness and Solar Radiation the infection index is calculated and depending on it warning is given.

- Warning is issued in the form of NO RISK, LOW RISK, and HIGH RISK.
- All the data recorded every second is saved in the excel sheet and graphs of severity index with respect to different parameters is plotted.
- Graphs verifying the equation representing coefficient of correlation and determination are plotted and equation of severity index is verified.

6. VALIDATION OF PARAMETERS AND RESULTS

S. No.	Validation Parameters	Results
1	Coefficient of correlation (R)	0.858647556
2	Coefficient of determination (R^2)	0.737275625
3	Mean Square Error (MSE)	0.146670464
4	Root Mean Square Error (RMSE)	0.382975801

For the used logistic regression model the coefficient of correlation (R) between the past experimental data and the output of the logistic regression model using the eq. 7.1 is 0.85867556 which shows that the two variables i.e. the severity index value of the past experimental data and the one calculated from the logistic regression equation. Coefficient of correlation determines the relationship between the mean values of the predicted value and the value of the past experimental data. The regression plot for the coefficient of correlation (R) is shown in the figure 7.6 which depicts the value R=0.85867556 which means that target linearly depends upon the output by approximately 85.86%. Figure 6.6 represents the residual plot between the observed and the predicted value at a particular temperature, relative humidity, rainfall, sunshine duration.

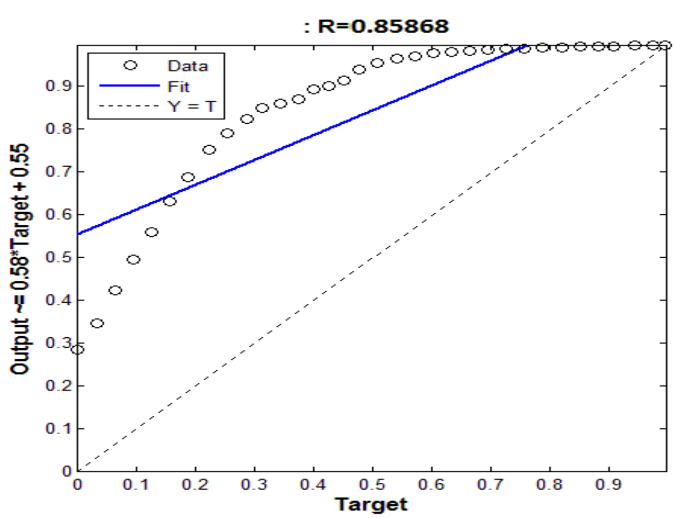

Fig. 6: Regression Plot for The Coefficient Of Correlation

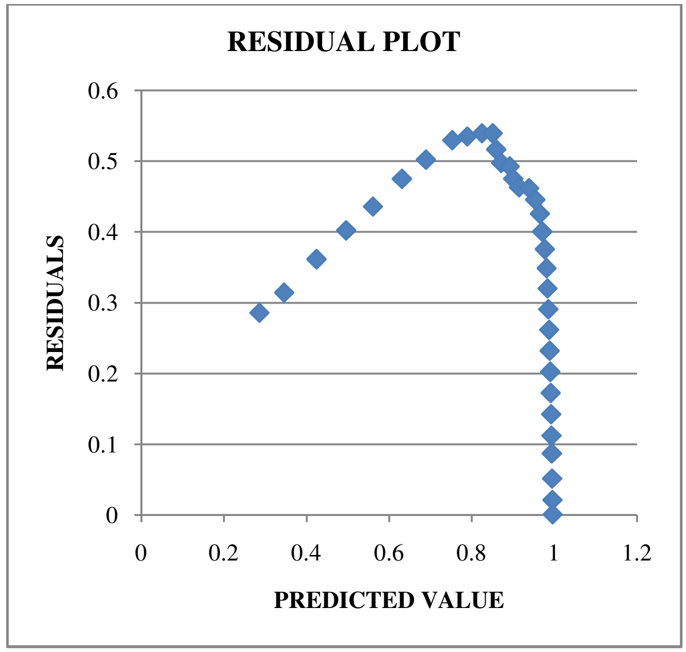

Fig. 7: Residual Plot For The Predicted Infection Index

The severity index plot of the past experimental severity index and the predicted severity index is shown in the figure 7.6, having severity index from the past experimental data on the *X* axis and the predicted value using the equation of logistic regression on the *Y* axis. This shows that the predictions made at the initial stages was having the drift from the past experimental index, which goes on reducing as the severity index approaches to the 1. This means that the accuracy of the prediction model increases as the severity index approaches the value of 1.

Figure 7.7 shows the error between the predicted values which we can say is the measured value and the past experimental value or we can say the true value

$$Error = Measured\ value - True\ value$$

Or

$$Error = Predicted\ value - Past\ experimental\ value$$

The error plot also supports our statement of the severity plot and show that the error reduces as the severity index approaches towards the 1.

7. CONCLUSION AND FUTURE SCOPE

In the present work a standard Logistic regression model has been developed to predict the risk. The infection can be predicted using four parameters. We successfully found the correlation between environmental parameters and infection index for wheat. The temperature graphs show that infection index increased with the temperature up to optimum temperature and after that it decreased. Wetness duration was directly proportional to the infection index and always increases with the wetness duration. Using these relation and past experimental data of parameters and infection index we developed a logistic regression model by calculating the model coefficient of general model equation to form a standard equation for wheat. For calculating the infection index and model coefficient we developed an interface that is a GUI using MATLAB tool. GUI gives the calculated value of model coefficient and model equation to derive the level of infection index within a second.

We can use logistic regression model for any crop. By instrumentation we can extract current data like current temperature and wetness duration to calculate infection index for that particular inputs. Further this system can be used as an alert system for the farmers. We can either send message or develop a website so as to warn the farmers about the risk when even there is a probability of risk occur.

Problem formulation:

The environmental impact of pesticides is often greater than what is intended by those who use them. Though there can be benefits using pesticides, inappropriate use can counterproductively increase pest resistance and kill the natural enemies of pests. The use of pesticides decreases the general biodiversity in the soil. Soil has been degrading because of the use of pesticides. Some pesticides contribute to global warming and the depletion of the ozone layer. Nitrogen fixation, which is required for the growth of higher plants, is hindered by pesticides in soil.

Pesticides can enter the human body through inhalation of aerosols, dust and vapour that contain pesticides; through oral exposure by consuming food and water; and through dermal exposure by direct contact of pesticides with skin. Pesticides are sprayed onto food, especially fruits and vegetables, they secrete into soils and groundwater which can end up in drinking water and pesticide spray can drift and pollute the air.

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