An Optimal Model Prediction for Fruits Diseases with Weather Conditions

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Abstract

This study provides the analysis and prediction of fruits diseases related to weather conditions (temperature, wind speed, solar power, rainfall and humidity) using Linear Model and Poisson Regression. The main goal of the research is to control the method of fruits diseases and also to prevent diseases using less agricultural pesticides. So, it is needed to predict the fruits diseases with weather data. Initially, fruit data is used to detect the fruit diseases. If diseases are found, we move to the next process and verify the condition of the fruits including their size. We identify the growth of fruit and evidence of diseases with Linear Model. Then, Poisson Regression used in this study to fit the model of fruits diseases with weather conditions as an input provides the predicted diseases as an output. Finally, the residuals plot, Q-Q plot and other plots help to validate the fitness of Linear Model and provide correlation between the actual and the predicted diseases as a result of the conducted experiment in this study.

Keywords : Poisson Regression | Linear Model | Weather Conditions | Plum Data

I. INTRODUCTION

At present, global warming is everywhere throughout the world. It effects environmental changes, weather changes, seasons changes and etc. Moreover, it also affects out living things and non-living things in the world. Because, if the weather changes, then it creates some abnormal situations i.e., forms more diseases even plants or animals or human beings in day-to-day life. Due to the weather changes, it creates more diseases into the plants and then also affects our production growth and profits. Perhaps, it will be continued then it affects our economy in the nation. So, this study focuses on analysing the fruits diseases with weather condition (temperature, humidity, wind speed, solar power, rainfall) using linear model and Poisson regression.

In the analysis of fruits diseases, the first stage is checking the occurrence of diseases in fruits with corresponding dates. So, in this process, simply identify the dates and diseases of fruits. If the diseases occurred in fruits, then move to the further process (second stage process) for checking the fruit size and etc. because of checking the fruits are affected by diseases or not. In this cases, implement the linear model to identify the growth of fruits size i.e. depends on the linear line whether the fruits size increases or decreases. So, in this process, using R^2 value to check the accuracy of the model fitted in fruits size and if the R^2 value is 1 (or close to 1) then it is the best model and also shows that perfectly fitted in fruits

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size. Finally, we check the residuals, QQ plots and leverage plots for the accuracy of model fitting and also identify the outliers in the Linear regression model.

The purpose (third stage process) of the Poisson regression is to predict the fruits diseases with the help of weather conditions i.e. temperature, humidity, wind speed, solar power, and rainfall. In Poisson regression, the weather conditions taken as input (Xs), actual fruits diseases as output (Y), processing the Poisson regression model and get the results of predicted fruits diseases. Afterward, we compared both the actual diseases and predicted diseases in fruits data with corresponding dates. In results and discussion, explained the result of linear model and Poisson regression model in plots and also explained the residuals, QQ plots, leverage plots, and correlation values. The testing data is plum fruits data, were collected from HeaRyong at Suncheon in Korea and the weather data were collected from Korea Meteorological Administration (KMA).

II. RELATED WORK

Sindhuja Sankaran and et al, had been published a review of advanced techniques for detecting plant diseases [1]. R. D. Berger has described the plant disease progress and then a comparison of the Gompertz and Logistic Equations [2]. L. V. Madden and G. Hughes, were examined the plant disease incidence: distribution, heterogeneity, and temporal analysis [3]. D. J. Butt and D. J. Royle, analysed the epidemiology of plant diseases using multiple regression analysis [4]. Rong Zhou and et al, examined the disease detection of cercospora leaf spot in sugar beet by robust template matching [5]. Roberto Oberti and et al, were examined the automatic detection of powdery mildew on grapevine leaves by image analysis [6]. A. K. Mahlein and et al, were analysed the development of spectral indices for detecting and identifying plant diseases [7]. H. Al-Hiary and et al, published the fast and accurate detection and classification of plant diseases [8]. T. Rumpf and et al, were analysed the early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance [9]. Vijai Singh and A.K. Misra, were examined the detection of plant leaf diseases using image segmentation and soft computing techniques [10]. Dae Sun Moon and et al, were published the development of artificial neural network based modeling scheme for wind turbine fault detection system [11]. Mrunalini R. Badnakhe and Prashant R. Deshmukh, had been published an application of K-means clustering and artificial intelligence in pattern recognition for crop diseases [12]. Based on these works, this study focuses on analysing and predicting for plum size and plum plants diseases with weather conditions using linear model and Poisson regression model.

A wireless sensor network is widely used to collect data from the environmental conditions and the data will be store an information storage [13]. It can be used for purpose of continuous monitoring of a specific environment like early detection of various diseases, industrial processes, health monitoring, agricultural, and etc [14]. so, in this case, the IoT is needed to connect the network connectivity and exchange data from one place to other place [15]. Enkhbaatar Tumenjargal and et al, published implementation of wireless PGN analyzer for ISOBUS network [16]. Jun Hyoung Kim and et al, had published the distance-based routing mechanism in mobile sensor networks [17]. So, depends on this reference, we used sensors for continuous monitoring the early detection of disease in fruits.

Linear Model

In statistics, linear regression is a linear approach for modelling the relationship between a scalar dependent variable denoted as Y and one or more explanatory variables denoted as X [18]. The case of one independent variable is called simple linear regression and more than one independent variables are called multiple linear regression model. The equation (1) of linear regression is,

$$Y = b_0 + b_1 X \quad (1)$$

Where, Y – response variable or dependent variable, X – independent variable, b_0 – intercepts, b_1 – slope of the line. Figure 1 diagram shows for the linear regression equation.

Poisson Regression

In statistics, Poisson regression is a generalized linear model form of regression analysis used to model count data and contingency tables [19]. Poisson regression also assumes the response variable Y has a Poisson distribution, and assumes the logarithm of its expected value can be modelled by a linear combination of unknown parameters [19]. Sometimes a Poisson regression model also called log−linear model. The general equation (2) for poisson regression is

$$\log(y) = a + b_1x_1 + b_2x_2 + \cdots b_nx_n \quad (2)$$

Where, y is the response variable, a and b are the numeric coefficients and, x is the predictor variable.

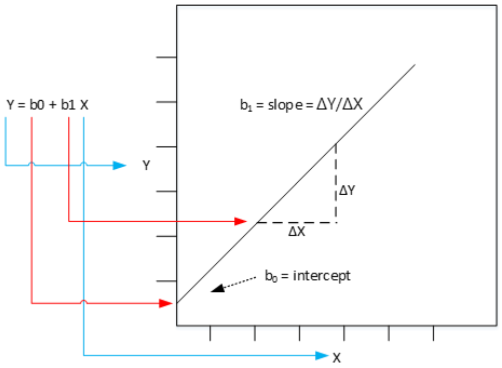

Fig. 1. Diagram shows for the linear model equation.

III. MATERIALS AND METHODS

In this work, the testing data is plum data and only one area i.e HaeRyong plum data at Suncheon city in Korea. The plum data consist of date, mean temperature, minimum temperature, maximum temperature, rainfall, windspeed, humidity, solar power, growth, plum width, plum length, and also several diseases, they are bacterial canker, anthracnose, powdery mildew, black leaf spot, sclerotinia sclerotiorum, screening of scab. The initial stage process is identifying the type of diseases occurred in plum data. The next stage of analysis is to check the plum fruits; whether the diseases are occurred or not by using linear model. The final stage process is to predict the plum diseases with weather conditions as inputs by using Poisson regression. In this process, we used different combination of input parameters for identify the appropriate prediction of disease in plum. Before that, in this section, we described a few kind of plant diseases, they are

3.1. Bacterial Canker

The common name is bacterial canker and the Scientific name is Pseudomonas syringae pv. Morsprunorum and p. s. pv. Syringae. Bacterial canker is a disease which affected in stem and leaves of prunus, especially in plums and cherries [20]. The main symptoms of bacterial cankers are sunken, dead patches of bark and small holes in leaves [20]. Figure 2 shows that the image of bacterial canker in plants.

Fig.2. Image shows for Bacterial Canker Diseases in Plant.

3.2. Anthracnose

The common name is anthracnose and the Scientific names are Colletotrichcum spp. / Gloeosporium spp. / Glomerella spp. / Sphaceloma spp. The anthracnose affects all plants at any growth stages and it affects the particular parts of plants are leaves, stems, petioles, pods, fruits and roots [21]. The symptoms are mostly visible on leaves and ripe fruits [21]. Figure 3 shows that the image of anthracnose in leaves.

Fig.3. Image shows for Anthracnose in leaves.

3.3. Powdery Mildew

The common name is powdery mildew and the various Scientific names, they are Phyllactina spp. / Leveillula sp. / Erysiphe spp. / Uncinula spp. / Blumeria spp. / Golovinomyces spp. / Podosphaera spp. / Sphaerotheca spp [22]. The powdery mildew is a fungal disease, which attacks the many plants (wide range of plants) and the main symptoms are

White, the dusty coating on leaves, stems, and flowers [22]. If left untreated and then it will affect more and more quickly spreading. Figure 4 shows that the image of powdery mildew in leaf.

Fig.4. Image shows for Powdery Mildew in leaf.

3.4 Black Leaf Spot

The common name is bacterial leaf spot and the Scientific name is Pseudomonas spp. The black leaf spot is bacterial diseases, which affects all growth stages of plants and affect part of the plants are leaves, stems, fruits, pods, and seeds [23]. If we untreated the disease, then it will develop more and more. Figure 5 shows that the image of black leaf spot in leaf.

Fig.5. Image shows for Black leaf spot in leaf.

3.5 *Sclerotinia Sclerotiorum*

Fig.6. Image shows for Sclerotinia Sclerotiorum in the plant (ref [22])

The preferred name is Sclerotinia Sclerotiorum and the other Scientific names are Peziza Sclerotiorum, Sclerotinia libertiana, Sclerotinia nicotianae, Sclerotium varium, and Whetzelinia sclerotiorum [24]. The eppo code is SCLESC. Sclerotinia Sclerotiorum is plant pathogenic fungus and it can cause disease called white mold if conditions are conducive [25]. It is also known as cottony rot, watery soft rot, stem rot, crown rot and blossom blight [25]. Figure 6 shows that the image for sclerotinia sclerotiorum in plant.

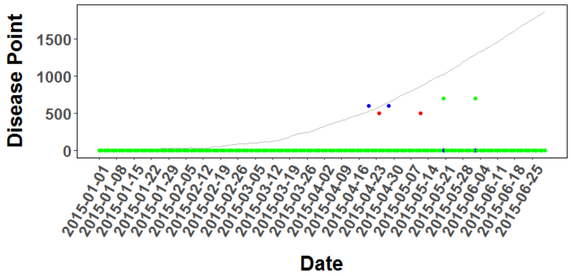

Fig.7. Diagram shows for Identified the disease point with their corresponding date.

Figure 7 shows for initial stage process i.e. identified the different type of diseases occurred in plum fruit with their corresponding date. In figure 7, there are three type of diseases occurred in plum fruits, they are Powdery Mildew (X2), Sclerotinia sclerotiorum (X6), and screening of scab (X7) with their corresponding colors are red, blue and green, respectively. The Powdery Mildew occurs on April 24th and May 11th, Sclerotinia Sclerotiorum occurs on April 20th and April 28th and the Scab occurs on May 20th and June 2nd. The grey color shows for cumulative temperature for plum data (checking the variation of temperature level).

IV. RESULTS AND DISCUSSION

In result, discusses the second and third stage process of analysing plum data. In second stage process, using linear model to check the plum size or plum fruit whether the diseases occur or not. The purpose of the second stage process is to check quantity of plum size. If any diseases occurs in plum size, then its reducing their quantity of plum fruit and also reducing their production & profits. So, it is important to analyse diseases in plum size. Figure 8 result shows for linear model in plum size. The x-axis has date i.e., from 9 April 2016 to 9 May 2016 and the y-axis have plum size in millimetre. In this plot, the grey dotted points are observed data (plum size) and a red line for linear regression. The red line growing upwards which shows that the plum size (fruits) are growing day by day in plum plants. Therefore, figure 8 result shows that the diseases are not affected in plum size or plum fruits.

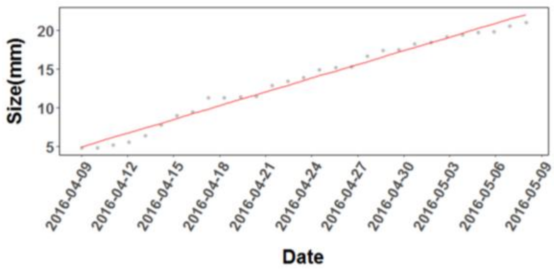

Fig.8. Result shows for linear model in plum size.

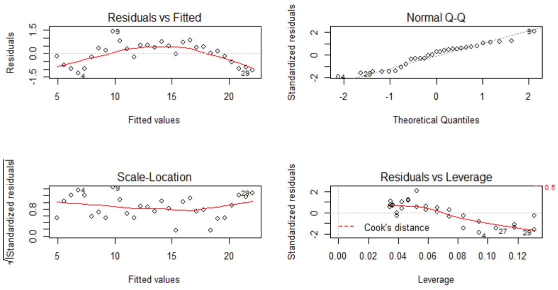

Fig.9. Result shows for checking the fitted Linear Model.

Next, need to check the linear model whether it is goodness of fit or badness of fit. Figure 9 result shows for checking the fitted linear model using residuals. In figure 9, the top−left plot shows for residuals vs fitted values i.e., the x−axis is fitted values and y−axis is residuals. This plot is used to detect the outliers, unequal variances, and non−linearity. The red line shows for non−linearity and so, the linear model is goodness of fit (if the red line is a linear then it is badness of fit). The top−right plot shows Normal Q−Q plot, the y−axis which consists of standardized residuals and x−axis have theoretical quantiles. The residuals points are close to dotted lines or on the dotted lines then the linear model is goodness of fit. The bottom−left plot shows that the scale location which is also called as spread location. So, in this plot the residuals are spread widely and the red line is same as horizontal line. So, this means the linear model is goodness of fit. If sometimes the residuals are not spread widely and the red line is same as vertical, then the model is badness of fit. The bottom−right plot shows residual vs leverage; which points have the greatest influence on the regression. The points 4, 27, and 29 are great influence on the linear model and the R^2 value is 0.98. Therefore, based on the checking in figure 9, then the linear model is fitted in goodness of fit.

The third stage process is to predict the diseases using Poisson regression model with a different combination of input parameters. The input parameters are temperature, rainfall, wind speed, humidity, and solar power and the output parameter is plum diseases. Figure 10 results shows for prediction of X2 disease with temperature and rainfall as input parameters. In this plot, x−axis have date from 1 April 2015 to 31 May 2015 and y−axis have X2 disease their values are 0 to 1 (0 means no diseases and 1 means diseases). The grey60 (black print: light color line) color refers to original plum diseases and red (black print: dark color line) color refers predicted plum diseases with a different combination of input parameters. The results show for comparing the original plum disease and predicted plum disease, if both are matched then the predicted of Poisson regression model is good.

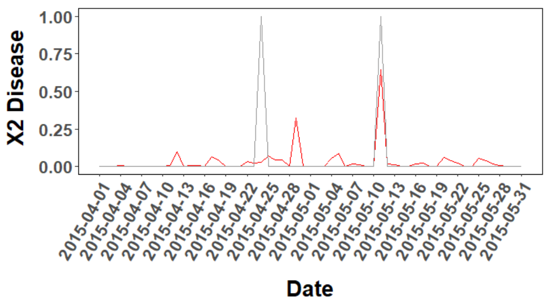

Fig.10. Result shows for prediction of X2 disease with temperature, rainfall and humidity as inputs.

Figure 10 result shows for prediction of X2 disease with three combination of input parameters namely, temperature, rainfall and humidity. So, this combination of input parameters provides a better result when compared to others. The correlation value of X2 disease is 0.61. If the correlation value is 1 or close to 1 then it is a best matching values. The Poisson regression equation of X2 disease is

$$\log(y) = 5.88 + (-0.087)x_1 + 0.13x_2 + (-0.16)x_3$$

Where, x_1 – temperature, x_2 – rainfall, x_3 – humidity, y – X2 disease.

Figure 11 result shows for prediction of X6 disease with different types of input parameters, they are temperature, rainfall, windspeed and solar power. The grey60 (black print: light color line) color refers to original plum diseases and red (black print: dark color line) color refers predicted plum diseases with a different combination of input parameters. The correlation value of X6 disease is 0.39.

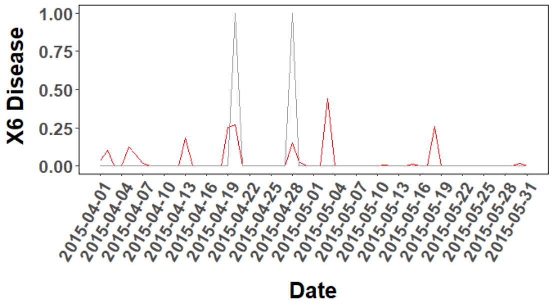

Fig.11. Result shows for prediction of X6 disease with different combination of inputs.

The Poisson regression equation of X6 disease is

$$\log(y) = -5.98 + 0.41x_1 + (-0.053)x_2 + (-0.32)x_3 + (-1.92)x_4$$

Where, x_1 – temperature, x_2 – rainfall, x_3 – windspeed, x_4 – solar power, y – X6 disease.

Table 1. Calculating the correlation value of disease with different combination of input parameters

Different Combination of Input Parameters	Diseases Correlation Values		
	X2 Disease	X6 Diseases	X7 Disease
T + R	0.42	0.06	0.10
T + W	0.06	0.07	0.13
T + H	0.00	0.38	0.29
T + S	0.09	0.35	0.16
T + R + W	0.43	0.15	0.16
T + R + H	0.61	0.38	0.29
T + R + S	0.44	0.37	0.16
T + R + W + H	0.60	0.37	0.42
T + R + W + S	0.41	0.39	0.99
T + R + W + H + S	0.59	0.38	0.99

Note: *T – Temperature, R – Rainfall, W – Wind speed, H – Humidity, S – Solar power.*

Table 1 shows for calculation the correlation value of disease (X2, X6 and X7) with different combination of weather data they are temperature, rainfall, wind speed, humidity and solar power. The maximum correlation value of X2 disease is 0.61 with their corresponding combination of input parameters are temperature, rainfall and humidity. In X6, the highest correlation value is 0.39 with their corresponding combination of input parameters are temperature, rainfall, wind speed, and solar power. In X7, the highest correlation value is 0.99 with their corresponding combination of input parameters are temperature, rainfall, wind speed, humidity and solar power. If the correlation value is 1 or close to 1 then the predicted disease of Poisson regression model is fitted. So, based on the result of correlation value the Poisson regression model get the sufficient result to predict plum disease. Because, in plum data which have very low amount of disease data, that is the reason didn't get the best result in Poisson regression model.

V. CONCLUSION

This study focuses on predicting the fruits diseases with weather conditions using linear model and Poisson regression model. In this study, there are three types of process, first stage process, second stage process and the third stage process. The first stage process is to check whether the diseases are occurred in fruits or not. Figure 7 shows the result of first stage process and the disease are affected in plum fruits. If the diseases are occurred in plum fruits, then move to next stage process. The second stage process is to check whether the diseases are occurred in plum size (plum fruits) or not. Figure 8 shows the result of second stage process and the diseases or not affected in plum size. The third stage process is predicting the plum diseases with different combination of weather conditions data in Poisson regression model. Table 1 explained the correlation value of disease X2, X6 and X7. So, based on these results to controlling method of plum fruits diseases and also to prevent diseases using less agricultural pesticides. Therefore, the same procedure can apply to other fruits diseases. In future, we will implement the neural network model to analyse and forecast of plum plant diseases.

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