Rice Blast Disease Forecasting for Northern Philippines

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Abstract: - Rice blast disease has become an enigmatic problem in several rice growing ecosystems of both tropical and temperate regions of the world. In this study, we develop models for predicting the occurrence and severity of rice blast disease, with the aim of helping to prevent or at least mitigate the spread of such disease. Data from 2 government agencies in selected provinces from northern Philippines were gathered, cleaned and synchronized for the purpose of building the predictive models. After the data synchronization, dimensionality reduction of the feature space was done, using Principal Component Analysis (PCA), to determine the most important weather features that contribute to the occurrence of the rice blast disease. Using these identified features, ANN and SVM binary classifiers (for prediction of the occurrence or non-occurrence of rice blast) and regression models (for estimation of the severity of an occurring rice blast) were built and tested. These classifiers and regression models produced sufficiently accurate results, with the SVM models showing a significantly better predictive power than the corresponding ANN models. These findings can be used in developing a system for forecasting rice blast, which may help reduce the occurrence of the disease.

Key-Words: machine learning, artificial neural network, support vector machine, rice blast disease

1 Introduction

Rice (Oryza sativa for Asian rice, or Oryza glaberrima for African rice) is an important food crop for many parts of the world. It has been estimated that more than 3.5 billion people worldwide depend on rice for more than 20% of their daily calories [1]. About 900 million of the world's population is considered to be dependent on rice as producers or consumers [2].

In the Philippines, there is a big demand for this crop because the average diet is based on rice [3]. In 2013 alone, the domestic consumption for milled rice in the country was reported to be 12.85 million metric tons [4]. A big part of the supply is produced in the northern provinces [5].

The rate of growth of rice production, however, has slowed down [7]. Rice crop loss is now one of the major concerns in rice production. Crop loss has become a great risk particularly for poor farmers with unfavorable environments, and on food security in general [2].

Of the various diseases limiting rice productivity, rice blast disease is an enigmatic problem in several rice growing ecosystems of both tropical and temperate regions of the world and has become a serious constraint in realizing the full yield potential of rice cultivars [6]. Rice blast disease causes between 11% and 30% crop loss annually. This represents a loss of about 157 million tons of rice.

The fungus Pyricularia grisea causes Rice blast, sometimes referred to simply as blast. In its sexual state, this fungus is also known as Magnaporthe grisea, and it feeds on the rice plant, causing severe damage. It attacks different parts of the plant: the collar, which can ultimately kill the entire leaf blade; the stem, which turns blackish and breaks easily (node blast); the neck of the panicle, where the infected part is girdled by a grayish brown lesion, or when severe, causes the panicles to fall over; or on the branches of the panicles which exhibit brown lesions when infected [8]. Blast is found in approximately 85 countries throughout the world. Its first known occurrence was as early as 1637 in China where the disease was known as rice fever disease [9]. Blast is highly destructive in lowland rice in temperate and subtropical Asia, and upland rice in tropical Asia, Latin America and Africa.

Although blast is capable of causing very severe losses of up to 100%, little information exists on the extent and intensity of actual losses in farmers' fields. Losses of 5-10%, 8% and 14% were recorded in India (1960-1961), Korea (mid-1970s), and in China (1980-1981), respectively. In the Philippines, yield losses ranging from 50-85% have been reported [10].

For the past 25 years, incredible advances have been made in studying the genetics of resistance to the blast disease. Using conventional genetic analysis of identified donors with resistance, availability of pure isolates of the blast pathogen and use of advanced molecular analysis techniques, about 60 genes for resistance have been identified. However, due to high variability in blast pathogens, most of the resistant varieties frequently succumb to this disease. The most feasible method for controlling blast epidemics is still the use of fungicides. Unfortunately, due to the high cost of chemicals, the use of fungicides is invariably uneconomic. Moreover, farmers sometimes skip the actual date of fungicide application due to lack of knowledge regarding the actual time of appearance of the disease [9].

Aside from the economic considerations, the hazards posed to farmers and to rice consumers by the use of fungicides make it desirable to minimize its use. In fact, many agricultural forecasting systems is to reduce fungicide use through its judicious use. For this purpose, an accurate prediction is crucial to properly time the application of disease control measures in order to avoid crop losses on one extreme, and over application of fungicide on the other extreme.

A prediction model based on the relationship between the environmental conditions and the severity of the occurring blast disease could be used to guide management decisions. Thus, if a sound forewarning system is developed, the explosive nature of the disease could be prevented by timely application of the control measures [6]. Such a system will be able to help not only reduce the cost of production but also promote the environmental safety for the operator and consumers by reducing chemical usage. Since weather plays a very important role in the appearance, multiplication and spread of the rice blast fungus, a weather-based forecasting system may provide the desired prediction accuracy [11].

In this study, we investigate the weather factors that correlate with the occurrence of rice blast disease in selected provinces in the Philippines, a tropical country. We further look at each of the individual growth stages of rice crop and explore the factors that may be used for building sufficiently accurate predictive models in each stage. ANN and SVM classifiers were built to predict whether or not rice blast will occur during a specific growth stage of rice crop and given the weather situation. ANN and SVM regression models for predicting the severity of an occurring rice blast disease were also implemented. Finally the expected accuracies of the built models were determined and statistically compared.

2 Related Literature

2.1 Weather variables in disease forecasting

Calvero et. al, explored the possibility of using weather factors with durations that allowed prediction of a blast severity or incidence before it actually occurred, using subsequent multiple regression models. Analysis was carried out with normal and transformed values both of the response (blast variables) and predictor variables (weather factors). In general, at Cavinti, the number of days with wind speed, mean maximum temperature, and precipitation frequency had correlated negatively with leaf blast. Similarly, precipitation frequency and total precipitation were negatively correlated with panicle blast. Weather factors such as mean relative humidity; mean solar radiation and consecutive days with precipitation [12]. In relation to our study, we considered other weather features and tried to reduce the dimensions to those involving only the significantly correlated weather features.

Chakraborty and Billard reported that there have been different attempts to describe the relationship between rice blast severity and environmental conditions in various countries. Majority of these attempts use empirical data and explanatory simulation models developed through the conventional regression analysis and multiple logistic regression. The use of artificial neural networks in a few studies has been reported to produce better results than the conventional methods [13].

2.2 Implementing machine learning algorithms in plant disease forecasting

The study of Kaundal et. al stated that diverse modeling approaches such as neural networks and multiple regression have been followed to date for disease prediction in plant populations. They pointed out that there is a need for exploiting new prediction software for better understanding of plant-pathogen-environment relationships because of their inability to predict values from unknown data points and longer training times [6]. In this study, we extend the modeling approach using support vector machines.

2.3 Implementing SVM Based System Using Fuzzy Directional Features

The study of Sadek et al, used a machine learning technique named Support Vector Machine to adopt an innovative approach for activity recognition in real-world scenes, where a new fuzzy motion descriptor is developed to model activities as time series of fuzzy directional features. They trained one-vs-all SVM classifiers on the features for activity classification [24].

2.4 Implementing machine learning for environmental safety

The use of machine learning algorithm specifically the support vector machine algorithm performed well in the pipeline defect detection in the study of Isa, Rajkumar and Woo. Oil and gas pipeline condition monitoring is potentially very challenging process due to varying temperature conditions, harshness of the flowing commodity and unpredictable terrain. Pipeline breakdown can potentially cost millions of dollars worth of loss and not to mention the serious environmental damage caused by the leaking commodity. The support vector machine algorithm was able to classify the signals as abnormal in the presence of wall thinning [22].

Likewise, the use of Artificial Neural Network which is another machine learning algorithm, was applied for the estimation of flashover voltage on polluted insulators. Kontargyri, Tsekouras, Gialketsi and Kontaxis trained a network to using MATLAB and designed a system in FORTRAN that gave a better result to estimate the critical flashover voltage even though they can not influence the learning rate variation [23].

2.5 Model Validation for Rice Blast Forecasting

Ramsey and Schafer used the PRESS statistic and cross validation procedure to test the predictive ability of the empirical models generated from regression analysis. With cross-validation procedure, 25% of the total observations were randomly chosen as validation set and were excluded in model development. The accuracy of the model prediction on a validation set was determined by computing the average prediction error (APE), i.e., the average difference of predicted from actual disease values. Regression equations with the smallest Predicted Error Sum of Squares (PRESS) values and Average Prediction Error (APE) close to zero were selected as the best empirical models in predicting blast [14]. The model validation or performance metrics that are used in our study are the Mean Squared Error and Coefficient of Determination.

2.6 Perceiving plant health condition

In another study about plant health condition, it was stated that detecting plant health condition is an important step in controlling disease and insect stress in agricultural crops [15]. In discriminating and classifying different fungal infection levels in rice (Oryza sativa L.) panicles, the researchers used artificial neural network and principal components analysis techniques. Four infection levels in rice panicles were considered: no infection condition, light and moderate infection caused by rice glume blight disease, and serious infection caused by rice false smut disease. Their results indicated that it is possible to discriminate different fungal infection levels of rice panicles under laboratory conditions using hyperspectral remote sensing data.

3 Methodology

3.1 Data Acquisition

Department of Agriculture (DA) Regional Unit 1 provided the data about rice blast occurrence for this research. This is the principal agency of the Philippine government responsible for the promotion of agricultural development in the selected northern provinces. The attributes of each report are the following:

• Report Date - the date of the cropping season when rice blast occurred

• Province - its specific Province

• Municipality/City-its specific Municipality/City

• Barangay - its specific Barangay

• Pest Observed - the kind of Rice Disease occurred

• Rice Crop Variety – the rice varieties approved by the National Seed Industry Council (NSIC), with rice blast resistance level (e.g., NSIC Rc 152 - Intermediate resistance to blast = 3)

• Growth Stage of the Plant - the stage when the rice blast occurred. The possible stages are (1) Seedling, (2) Tillering, (3) Maximum Tillering, (4) Panicle Initiation, (5) Heading/Flowering, (6) Milking and (7) Ripening.

• Severity - the percentage of harshness of the rice blast within the area.

The history of weather conditions was gathered from the different Agromet and Weather stations of Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA) from the following stations:

• Sinait PAGASA Station

• Dagupan PAGASA Station

• DMMMSU Agromet Station

• MMSU Agromet Station

The historical weather data spanned the period of January 2006 to December 2013, and the attributes contained are the following:

• Evaporation - vaporization of a liquid per month (in millimeter)

• Temperature (Max) - maximum temperature averaged for the month (in Celsius)

•Temperature(Min)- minimum temperature averaged for the month (in Celsius)

• Wind Speed – average air speed per month (in km per day)

• Rainfall - the average precipitation count for the month (in millimeter)

• Solar Radiation - average radiant energy emitted by the sun (in kW/m2)

• Brightness - average brightness per month (in minutes)

• Humidity-average amount of vapor in the air for the month (in percentage)

3.2 Data Processing

The data acquired from DA and PAGASA were combined into 1 table using synchronization. Specifically, for each row of the DA data describing a specific rice blast report, the corresponding weather information from PAGASA was appended. This resulted in a data set consisting of 153 rows and 16 columns.

After the synchronization, feature scaling was applied to make sure that the disease and weather features are in similar scale. The mean normalization was applied to scale the features, where the general rule is to take a feature value $\chi_{i,j}$ (at row i, column j) and replace it with a new value using the formula

$$f(x_i, j) = \frac{x_i - \mu_j}{s_j} \quad (1)$$

Where μ_j and s_j are the average and standard deviation, respectively, of all $\chi_{i,j}$ values within column j of the data set. The resulting scaled features values were in the range $-3 \leq f(\chi_{i,j}) \leq 3$.

Using the resulting synchronized data; Principal Component Analysis (PCA) was applied to estimate the most important weather features in the occurrence of rice blast. PCA is a statistical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components as used in the study of Zhang et al [25].

After we determined the most important features, we characterized the factors that affect the occurrence of rice blast within each Growth Stage of the Plant (GSP). The results of this characterization can be used in giving advice to farmers and other agricultural organizations and operators on when it would be wise to apply some interventions (e.g.

application of fungicides, etc.) to reduce the risk of rice blast. In relation to this task, we created binary classification models for the prediction of the occurrence or non-occurrence of rice blast, within each growth stage of the rice crop. For this purpose, additional rows in the data set were inserted to represent instances when rice blast did not occur. We also implemented regression models to predict the severity of an occurring rice blast. The classification and regression models built in this study are based on the Artificial Neural Network (ANN) and Support Vector Machine, which are briefly described in the following sections.

3.2.1 The Artificial Neural Network

ANNs offer a computational approach that is quite different from conventional digital computation. Mehrotra stated that digital computers operate sequentially and can do arithmetic computation extremely fast [16]. Biological neurons in the human brain are extremely slow devices and are capable of performing a tremendous amount of computations necessary to do everyday complex tasks, common sense reasoning and dealing with fuzzy situations. The underlining reason is that, unlike a conventional computer, the brain contains a huge number of neurons (information processing elements of the biological nervous system) acting in parallel. ANNs are thus parallel, distributed information processing structures consisting of processing elements interconnected via unidirectional signal channels called connection weights. Although modeled after biological neurons, ANNs are much simplified and bear only superficial resemblance. Some of the major attributes of ANNs are: (1) they can learn from examples and generalize well on unseen data and (2) are able to deal with situation where the input data are erroneous, incomplete or fuzzy [17].

The process of finding the best set of weights for the neural network is referred to as training or learning. The approach used by most software to estimate the weights is backpropagation. Each time the network cycles through the training data, it produces a predicted value for the target variable. This predicted value is compared to the actual target value, and an error is computed for each observation. The errors are fed back through the network and new weights are computed to reduce the overall error. Despite the neural network terminology, the training process is actually a statistical optimization procedure. Typically, the procedure minimizes the sum of the squared residuals.

From this model (refer to Figure 1) the interval activity of the neuron can be computed using the formula:

$$V_k = \sum_{j=1}^{p} W_{kj} \; X_j \qquad (2)$$

An activation function is then applied to the resulting value of V_k to produce the output value y_k. In this study, the activation function used was the sigmoid function.

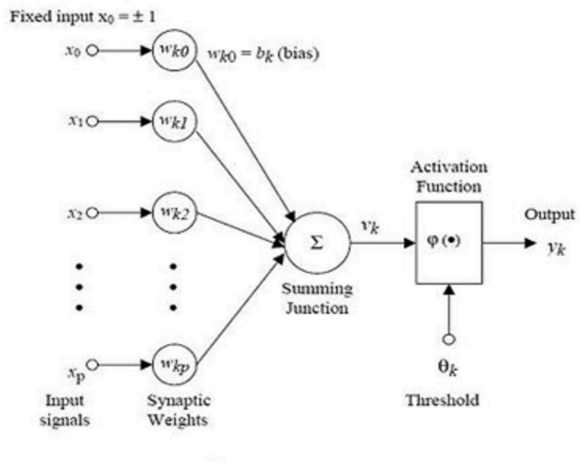

Figure 1: Artificial Neural Network [19]

3.2.2 The Support Vector Machine

Support Vector Machine (SVM) is a family of algorithms that have been implemented in various computation problem domains such as classification, recognition, regression and time series. SVM originated as an implementation of Vapnik's (1995) Structural Risk Minimization (SRM) principle to develop binary classifications. SVM emerged from research in statistical learning theory on how to regulate generalization, and find an optimal trade-off between structural complexity and empirical risk. SVM classify points by assigning them to one of two disjoint half spaces either in the pattern space or in a higher-dimensional feature space. The main idea of SVM is to construct a hyperplane as the decision surface such that the margin of separation between positive and negative examples is maximized (see Figure 2)[18].

Support Vector Machines also have well understood solutions and a theory (called maximum margin) that directly addresses generalization (good predictions on new data). Kernel Methods (both as used in SVMs and elsewhere) allow controlled introduction of very complex functions. Kernel function in SVM is used to map the training data into kernel space. This is typically done for data sets that are not linearly separable in the current space, because mapping the data points to a higher dimension makes it more possible to find a good separating hyperplane. In our study, we used the sigmoid kernel for the SVM classifier and the polynomial kernel for the SVM regression model.

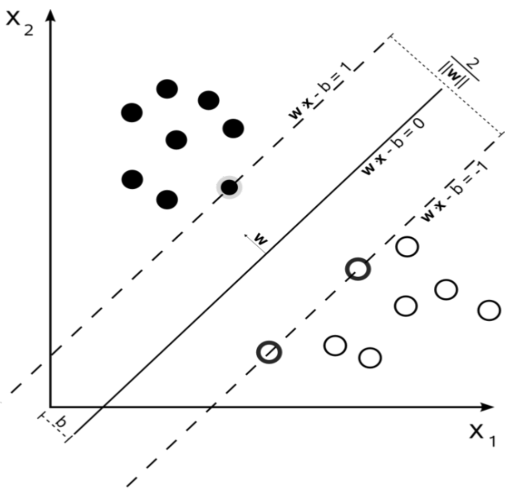

Figure 2: Support Vector Machine [20]

3.3 Data Analysis

To support the characterization of each growth stage of the rice crop, binary classification models were created. The accuracy was measured for the two machine learning algorithms to determine the occurrence or non-occurrence of rice blast disease as shown in Eq. 3,

$$Acc = (TP + TN)/(TP + FP + FN + TN) \quad (3)$$

where *TP* is the number of True Positives, *TN* is the number of True Negatives, *FP* is the number of False Positives and *FN* is the number of False Negatives for each growth stage of the rice crop.

To generalize the results for each machine learning algorithm, the sample from the population underwent cross validation which is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction and forecasting, and one wants to estimate how accurately a predictive model will perform in practice. The idea behind k-fold cross-validation is to divide all the available data items into roughly equal-sized sets. Each set was used exactly once as the test set while the remaining data was used as the training set [21]. In this study, we used k = 10.

For performance with respect to predicting severity, the Mean Squared Error (MSE) and the Coefficient of Determination (R2) values were computed.

Mean squared error quantifies the difference between values implied by an estimator and the true values of the quantity being estimated. This value is computed using the following formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (X_i - Y_i)^2 \quad (4)$$

where *X* is the vector of n predictions and *Y* is the vector of true values. Lower MSE values are better, and zero means no error.

Likewise, the coefficient of determination, R^2, is simply the square of correlation coefficient, but it is very useful because it gives the proportion of the variance (fluctuation) of one variable that is predictable from the other variable. It is a measure that allows us to determine how certain one can be in making predictions from a specific model. The coefficient of determination is such that $0 \leq R^2 \leq 1$, and denotes the strength of the linear association between *X* and *Y*. It represents the per cent of data that is the closest to the line of best fit. It is computed using Eq. 5

$$R^2 = 1 - \frac{SS_R}{SS_T} \quad (5)$$

where SSR is the regression sum of squares and SST is the total sum of squares.

4 Results and Discussion

This section covers the presentation and discussion of the results and some analyses of the feature selection, quantitative description/characterization of each growth stage and performance outputs of the two machine learning algorithms.

4.1 Feature Selection

From the results of the PCA, which was used to explore the most important features that affect the occurrence of rice blast, Rainfall accounts for 48% importance in the occurrence of rice blast, with Temperature Minimum (31%), Temperature Maximum (17%) and Humidity (3%) as the next most important features (see Fig. 3). On the other hand, Solar Radiation, Evaporation, Brightness and Wind Speed have very low and/or minimal influence (<1%), and can therefore be omitted.

With this result, the most important weather features aggregated per month are synchronized with the rice disease reports, resulting in a 153 x 5 matrix that describes the synchronized data set. Specifically, the following attributes were used in the characterization of factors for each growth stage and predicting the severity when the rice blast occurred:

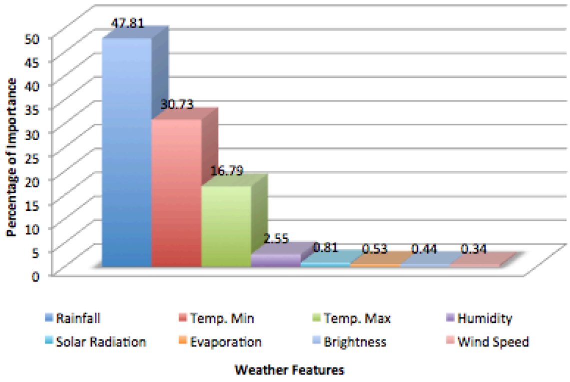

Figure 3: Principal Components of rice blast occurrence

4.2 Growth Stage Risk Characterization

From the synchronized data set from weather and rice blast reports, a simple histogram in Fig. 4 shows that Growth Stage 2 (Tillering) is the growth stage most prone to rice blast with more than 45% of the total reported occurrences, while Stage 7 (Ripening) has no occurrence of rice blast. With this information, a sound characterization of each growth stage can be explored further. This can help farmers and agricultural organizations to decide on when it would be most judicious to apply intervention to minimize the possibility of occurrence of rice blast.

Tables 1 and 2 show quantitative descriptions for each growth stage for the most important factors in the occurrence of rice blast, wherein the maximum and minimum values are revealed. For Stage 1 (Seedling), rice blast will most likely occur if Rainfall is within 14.1-36.4mm, temp. min. is within 23.6-24.1◦ C, temp. max. is 31.5-33.1◦C, and Humidity is 86-87%. Non-occurrence of rice blast observed Rainfall was in minimum count that has an average of 3.56 days per month, while temperature is much higher and Humidity decreased to about an average of 83%.

In Stage 2, which is the most prone to rice blast, the range of Rainfall is within 0-32.4 mm, Temp. Min. is within 16.9-24.9◦ C, Temp. Max. is 30.8-33.1◦ C, and Humidity is 83-87%. For the years with non-occurrence of rice blast, an average Rainfall count of 0.35, and Humidity at an average of 83% was observed which are lower than the minimum values.

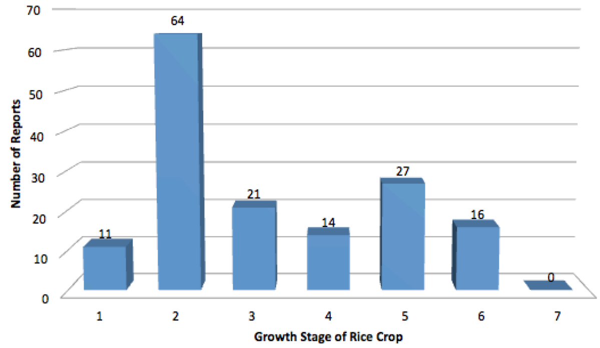

Figure 4: Histogram of number of rice blast reports on each stage

GSP	Rainfall		Temp Min	
	Min	Max	Min	Max
1	14.1	36.4	23.6	24.1
2	5.6	32.4	16.9	24.9
3	0.0	29.6	16.9	24.1
4	10.5	32.4	16.9	24.6
5	0.0	12.1	16.9	24.9
6	0.0	19.4	18.4	24.6

Table 1: Characterization of factors for each Growth Stage of the Plant - Humidity and Temperature Min

GSP	Temp Max		Humidity	
	Min	Max	Min	Max
1	31.5	33.1	86	87
2	30.8	33.1	83	87
3	30.8	33.1	84	87
4	30.8	32.2	83	86
5	30.8	33.3	84	87
6	31.0	33.2	85	87

Table 2: Characterization of factors for each Growth Stage of the Plant - Temperature Max and Humidity

For Stage 4, Rainfall is within 10.5-32.4mm, Temp. Min. is within 16.9-24.6◦C, Temp. Max. is 30.8-32.2◦C, and Humidity is 83-86%. In the cropping season with no occurrence of rice blast in this stage, it was observed that Rainfall again was below the minimum count with an average of 5.66 mm per month.

For Stages 3, 5, and 6, the occurrence and non-occurrence of rice blast has no significant difference associated with the weather variables observed.

4.3 Binary Classification of the Rice Blast Disease

In line with the values in the characterization for each growth stage of the rice crop, weather features and rice crop variety resistance values for occurrence and non-occurrence were inputted in the machine learning algorithms for the binary classification for each growth stage of the rice crop. Table 3 shows the results on the accuracy of each of the two algorithms. Both the ANN and SVM classifiers produced an average accuracy above 90%, with the SVM scoring at least 93% on each of the different growth stages. Using paired t-test in the results statistically show that the difference of the accuracy of the machine learning algorithms is significant (p-value < 0.01). This implies the built SVM classifier is significantly more accurate than the corresponding ANN classifier. Thus, the SVM classifier is strongly recommended in the development of an application to classify whether rice blast disease will occur or not occur.

For Stages 3, 5, and 6, the occurrence and non-occurrence of rice blast has no significant difference associated with the weather variables observed.

GSP	ANN	SVM
1	92.89	96.78
2	89.69	93.69
3	91.64	96.50
4	92.43	97.54
5	93.68	97.41
6	93.59	96.74
Average	92.32	96.44

Table 3: Accuracy of Binary Classification for ANN and SVM

4.4 Prediction of Severity using ANN and SVM

Table 4 shows the comparison of the ANN and SVM for prediction of rice blast severity using Mean-Squared Error (*MSE*) and Coefficient of Determination (R^2) based on the results of a 10-fold cross-validation. For the MSE, the algorithm with a value closer to zero gains an advantage over the other algorithm. A paired t-test of the cross-validation results with a 0.05 significance level indicate that the MSE value for SVM is significantly lower (p-value < 0.001) than that of ANN.

The coefficient of determination gives the proportion of the variance (fluctuation) of one variable that is predictable from the other variable, where an R^2 of 1 indicates that the regression line perfectly fits the data. In this measure, the SVM result is likewise better than that of ANN. Also, applying a paired t-test (with 5% significance level) shows that the difference is significant (p-value < 0.02).

Fold Num	ANN		SVM	
	MSE	R^2	MSE	R^2
1	0.5162	0.3140	0.2453	0.8634
2	0.5440	0.5407	0.2640	0.7742
3	0.5184	0.5407	0.1730	0.7274
4	0.3569	0.3984	0.2524	0.8477
5	0.5974	0.5028	0.1577	0.5436
6	0.4225	0.6808	0.2640	0.9379
7	0.3770	0.5311	0.2650	0.7370
8	0.3887	0.9075	0.2507	0.5490
9	0.5498	0.1229	0.2508	0.8490
10	0.3950	0.1680	0.2507	0.9290
Average	0.4666	0.4707	0.2374	0.7758

Table 4: Mean squared error (*MSE*) and Coefficient of determination (R^2) performance of ANN and SVM

5 Conclusions

Considering the different weather variables that contribute to the occurrence of rice blast disease, the most important features are Rainfall, Temperature Minimum, Temperature Maximum and Humidity, when explored using Principal Component Analysis. Also, the characterization of these features show that non-occurrence of rice blast has values lower than the minimum expected values for the most important weather feature, which was supported by the accuracy metrics in the binary classification using ANN and SVM models. Likewise, investigation on the regression problem as considered in the severity of rice blast when occurred, the SVM model provided a more accurate prediction with an average *MSE* of 0.2374 and R^2 of 0.7758 which is significantly better than the ANN model. Therefore, the SVM models for classification and regression problem indicated in this study can be used in the development of software to predict whether a rice blast will occur and how severe will it be. This information may now help the farmers and other agricultural organizations in the control and management of rice blast disease such as providing interventions (e.g. application of fungicides, better cropping season, etc.), that can help in improving food security most especially in developing countries such as the Philippines. However, the effect of the climate change can be further explored to relate the factors of climate change and its effect on rice blast disease.

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