www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277- 7695
ISSN (P): 2349-8242
NAAS Rating: 5.23
TPI 2021; 10(6): 1060-1069

www.thepharmajournal.com
Received: 02-04-2021
Accepted: 10-05-2021

Moin Kabir
M.Sc. Student, Department of Plant Pathology, Lovely Professional University, Jalandhar, Punjab, India

Meenakshi Rana
Assistant Professor, Department of Plant Pathology, Lovely Professional University, Jalandhar, Punjab, India

Ankita Roy
M.Sc. Student, Department of Genetics and Plant Breeding, Lovely Professional University, Jalandhar, Punjab, India

Corresponding Author:
Ankita Roy
M.Sc. Student, Department of Genetics and Plant Breeding, Lovely Professional University, Jalandhar, Punjab, India

Insight of rice disease forecasting models

Moin Kabir, Meenakshi Rana and Ankita Roy

Abstract
Rice endures from several fungal and bacterial diseases in India. A tremendous amount of yield loss takes place due to the attack of pathogens on rice. For secure management relying on the environment and pathogen relation, multiple forecasting models have been developed Seens many years ago, rice diseases rice blast, rice sheath blight, rice leaf spot, EPIBLAST, BLASTL, EPIRICE, BLIGHTASIRRI, some forecasting model build upon calculation from the vertical and horizontal measurement which sustain temperature combination, relative humidity, sclerotia present, and tiller. Other models are calculated on temperature, dew period, meteorological input variables, sporulation, inoculum potential, conidia release, penetration, incubation period, etc. Blast regarding meteorological study progressed at the central rice research institute. Obtained data have shown that the application of fertilizer based on forecasting of disease helps in effecting control of infection. The determining model conceded that 52 studies have been recorded. The best consistent input variable is air temperature, persist by rainfall and relative humidity.

Keywords: Rice diseases, yield loss, forecasting model, sustain, meteorological study, control of infection

1. Introduction

Rice (*Oryza sativa*) is one of the most world's staple food crops. Rice production in India concerning 131,274,000 tonnes. it is predominant in Asia, Rice crop is additionally raised in Europe since the fifteenth century, chiefly in the Mediterranean countries collectively with Italy, Portugal, Spain, France, and Greece. Major worldwide production has taken place once the wheat crop. nowadays rice crops square measure attacked by several pathogens, most of the outstanding diseases countered on rice plants square measure Rice blast (Pyricularia oryzae teleomorph Magnaporthe grisea), Rice leaf blast, Rice sheath blight (Rhizoctonia solani), microorganism grain rot (*Burkholderia glumae*) of rice. Blast flora will harm the plant at any stage of its life cycle.

Moderate field infections will cause, five hundredth grain yield reduction that equals to food expendable by sixty million individuals (Devi and Sharma, 2010), though blast is that the most dangerous one. Blast infectious agent developed mechanism for spore attachment on the leaf surface, unwellness disagree in cool temperature and high wet condition P. Oryzae conidia do not germinate on direct daylight. Survival reduced staggeringly in winter, however, monogenesis occurred throughout the spring season on the plant rubble. Major diseases yield loss completely different in many places although we all know that some fluctuation and weather truth will modification the infectious agent activity. meantime loss caused by BGR up to four-hundredth in Lauisinia and seventy-fifth loss in grain yield according to in Vietnam. Yield loss because of sheath blight as high as 2 hundredth & affected concerning 120,000 – 190,000 hectares.

Rice sheath blight is an Associate in Nursing increasing concern for rice production, particularly in intense production systems in Japan. twenty-fifth yield loss according to if the flag leaves square measure infected. The main motive to develop this foretelling model is to realize the correct life of yield loss or however an important weather scenario has its result on infectious agent development on the plant. though we are able to say relation dependency of the infectious agent and host interaction in natural field condition. unwellness foretelling permits prediction of probable outbreaks or will increase in unwellness intensity, permitting if, when, and wherever a specific unwellness management follow ought to be applied.

The main aim of forecasting to disease recognition, diseases assessment and yield fall, pathogen dispersal, modeling and data analysis. All these conditions of disease epidemiology are required components of forecasting systems. However, we should practice forecasting because the perception is that we have active control methods at our disposal through the use of resistant cultivars, cultivar diversification, eradication, exclusion, and chemicals. Chemical management methods come in various guises, from soil sterilization and seed cure to foliar sprays. These are sometimes expensive but easy to apply through mechanized equipment and they give acceptable disease control (Lee, 2015) [10].

Weather-based forecasting schemes ranges back the rate of production by optimizing the materialistic arrangement and density of application of administration measures and assures operator, costomer and environmental security by lessening of chemical usage.

Plant disease forecasting dates back into the prehistoric of man, miller. started that the first written reference to plant disease forecasting was mentioned in the ancient Sumerian text on the cultivation of barley and its 'Samana disease. over the last fifty years, several different disease forecasting schemes have been developed and refused by trial-and-error methods.in japan rice leafhopper & rice blast epidemics in 1940 resulted in a great loss of rice yield & become a direct motive to start a nationwide forecasting system in 1941.

Predictive models need local climate input. Initial implementing efforts are sustained by industry, researchers and extension agents through field working days, demonstrations, and on- farm trials. Farmers and pest control counselors can require it for enhancing of crop management (Srivastava, 2017) [16].

Approaches

Disease forecasting needs field observations on the infectious agent characters, an assortment of weather information, a form of the crop and bound investigations and their correlations. Usually, the subsequent strategies are established in disease foretelling.

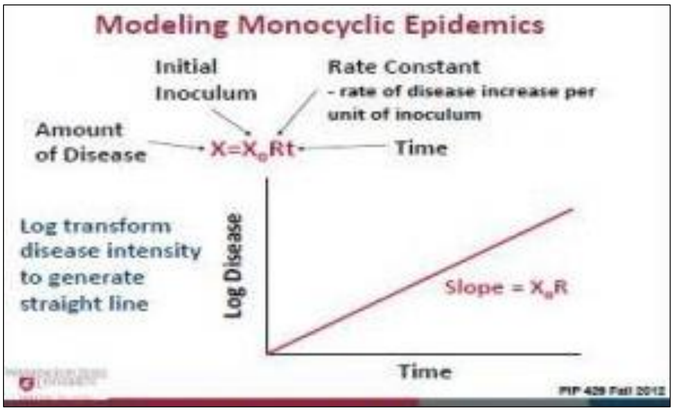
The presence of primary inoculant density and viability are determined within the air, soil, or planting material. prevalence of viable spores or propagules within the air, it is assessed by using mistreatment different air housings devices (spore traps). within the case of soil-borne diseases, the first inoculant within the soil is determined by the monoculture technique. The presence of Rice leaf blast, loose smut of wheat, ergot of pearl millet and infective agent diseases of potato is detected within the seed heaps at random by different seed testing strategies. Seed testing strategies are accustomed to confirm potential disease malady incidence and change calls to be created on the necessity for chemical seed treatment. The extent of many virus diseases relies on the severity of the preceding winter that affects the scale of vector population within the season. e.g., Sugarbeet yellows virus.

Weather conditions like temperature, ratio, relative humidity, rainfall, light, wind rate, etc., throughout the crop season and through the lay crop season are measured. atmospheric conditions higher than the crop and at the soil surface also are recorded (Katsantonis, 2017) [4].

Weather information of many years is collected and related to the intensity of the diseases. The information is compared and so the forecasting of the disease is completed. Forecasting criteria developed from comparisons of disease observation with customary meteoric information are provided for diseases like Septoria leaf blotch of wheat, fire blight of apple, and barley powdery mildew.

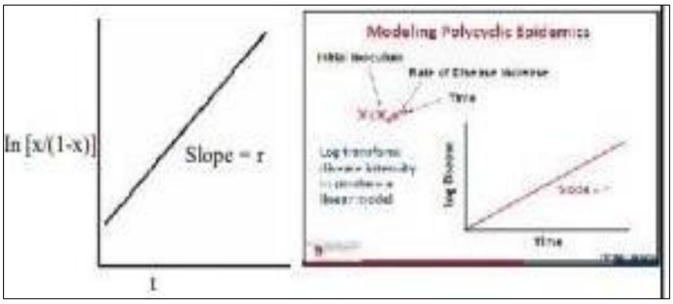
In some advanced countries forecasting of disease is formed by the employment of computers. This technique supplies the results quickly. One such computer-based mostly programmed BLIGHTAS that developed supported the quantitative relation of the peak of the lesions to the plant height and percentage of the number of pathologic hills.

Two main supports for models,



***Source*:** Kim, C. K. (1987) [7].

Fig 1: Modeling of monocyclic diseases



***Source*:** Kim, C. K. (1987) [7].

Fig 2: Modeling of polycyclic diseases

Table 1: Rice Disease Models

S. No	Model	Country	Forecast	Developed By	Year
1	Epiblast	Korea	Rice leaf blast	Kim &Kim	1993 [8]
2	Blastam	Japan	Rice leaf blast	Koshimizu	1982
3	Blastl	Japan	Rice leaf blast	Hashimoto *et al.*	1984
4	Blightas Blightasrri	Philippines	Rice sheath blight	Ijiri & Hashiba	1986
5	Epirice	Korea	Leaf spot, brown spot, bacterial blight, sheath blight, and rice tungro	Savary	2012
6	BGRcast	Korea	Bacterial grain rot	Yong hwan Lee *et al.*	1998-2004an d2010

Epiblast: forecasting was field-proven during the 1991 cropping period. EPIBLAST anticipates the peak of the leaf blast epidemic as early as the intermediate of July. this forecasting model was developed for forecasting the incidence of leaf blast disease. This model depends on field rice blast meteorological and epidemiological data. EPIBLAST model includes three groups of input variables 1. Meteorological (temperature, RH, rainfall, wind pace, and

dew period); 2. epidemiological processes (inoculum potential, sporulation, conidium release, and dispersal, penetration, and incubation cycle); 3. Plant physiological state (healthy, diseased, and dead leaf area), the validity of this model was accurate Seens up to the year 1991. There are several models developed for leaf rice blast these all are developed (Blastam, Blastl) based on epidemiology and accurate is modern models are committing hugely on the epidemiology of the disease. Blast infection is inordinately difficult to eliminate from the field because of the intricacy in the disease cycle of its pathogen. We cannot expect a fully developed model is adaptable another similar kind of disease problem on another place, the weather condition is different from each other and epidemiology though. The majority of published models were developed to forecast leaf blasts. Forecasting of leaf blast.
was crucial for early blast control, societies where the disease arises early in the developing season. Just more than a third (37%) of the blast figure could project both leaf and neck blast. Thus, the prediction of neck blast accuracy was reported to be low. Very few forecasting models are applying nowadays by rice growers from 52 published models (Sella, 2021) [14].

Mars: (monitoring agricultural resources) model is currently available in Europe developed by Kaundal *et al* (2006) [5, 6], Kang *et al*. (2010), and Kanda (2012), MARS model would be managed by joint Research Center at Ispra (Italy). The system incorporates information from 1450 European durability stations and satellites.

Epirice: is a well-known forecasting model to predict five major epidemic diseases that occur globally. EPIRICE encompassed contrasting hierarchy levels of growing leaves, tillers, plants, crop stands, world regions and the world. The model was related to GIS (geographic information system), daily historic weather and crop installation data of two years, other variables were sites, crop growth, infection rate, age effect, epidemic onset, residence times, aggregation, temperature effect, and wetness effect.

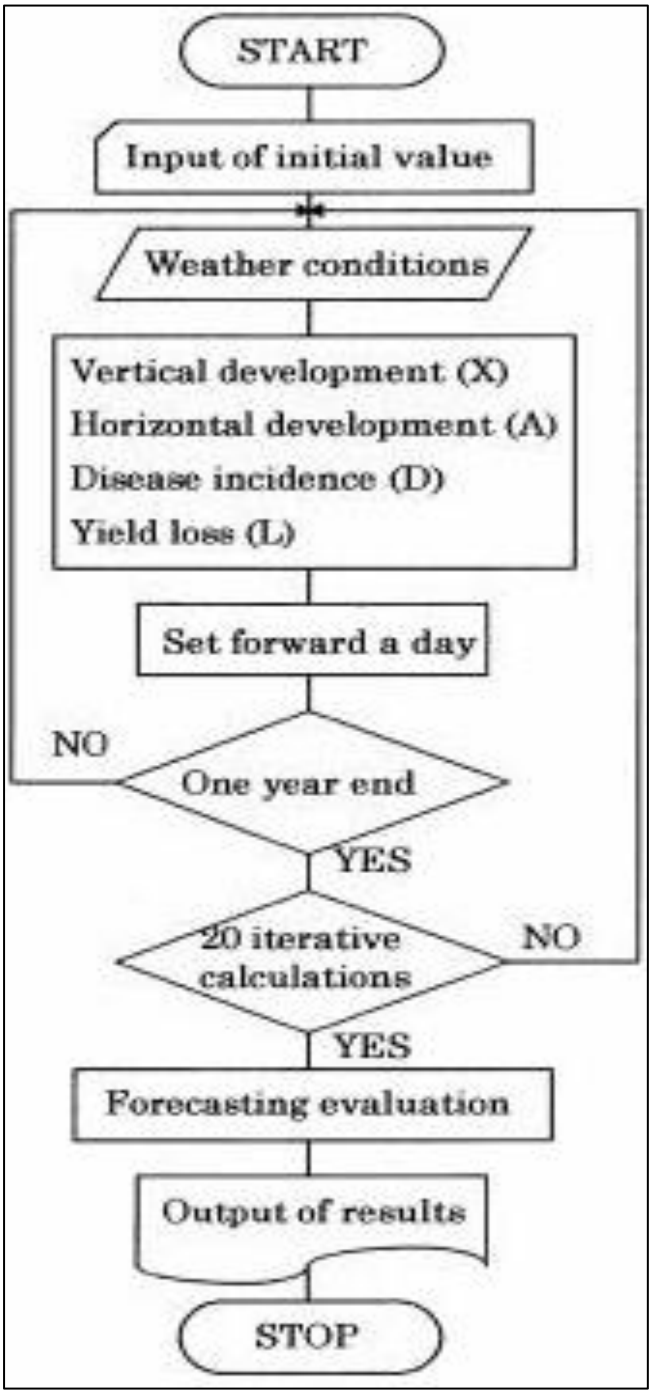
Blightasirri: a computerized forecasting model system developed under Hashiba *et al*. (1986). BLIGHTASIRRI model would be written in Microsoft FORTRAN, application based on Disk Operating System (DOS). this model depends on the observation of cultural conditions of the field which is carried out at the International Rice Research Institute (IRRI), examination of disease development, disease incidence (statistical) weather observation (temperature, relative humidity) measurement of the temperature and relative humidity of the atmosphere based on the weather data published at the wetland, IRRI climate unit. The spreading of rice sheath blight was classified into vertical and horizontal development. Vertical development affected by the temperature and relative humidity as meteorological variables and the susceptibility of leaf sheath as host conditions, while horizontal development is influenced by the temperature and relative humidity, as meteorological variables, and the number of sclerotia and tillers as host and pathogen condition. BLIGHTASIRRI gives the result of forecasting sheath blight disease and method of estimating yield loss. Experiment using 1700 (1429 foreign cultivars from more than 40 countries and 277 domestic cultivars) rice cultivars.

Blightasirri: model experiment categorizes on the vertical development of sheath blight legion on rice & horizontal development of sheath blight on rice. Vertical lesions development examined in two conditions; one is grown variety (koshijiwase) in field & another measured under normal natural temperature & relative humidity. In another words horizontal disease development as expressed by the percentage of the number of diseased hills was examined with koshijiwase growing in field under natural temperature and relative humidity. A model curve captured the development of disease as a function of temperature relative humidity and density of sclerotia. Both models are represented on the curve. The quantity of existing sclerosia does influence the rate of horizontal development of disease (Singh, 2019) [15].

Daily average temperature (°C)	Vertical and horizontal development in a day[a)]
19.0	0.27
19.5	0.40
20.0	0.48
20.5	0.64
21.0	0.70
21.5	0.81
22.0	0.90
22.5	1.02
23.0	1.13
23.5	1.18
24.0	1.24
24.5	1.29
25.0	1.35
25.5	1.39
26.0	1.43
26.5	1.47
27.0	1.51
27.5	1.55
28.0	1.58
28.5	1.56
29.0	1.55
29.5	1.53
30.0	1.50

***Source*:** Kobayashi, T., IJIRI, T., MEW,

Fig 3: Vertical and horizontal expansion of the lesions on rice plants infected by Rhizoctonia solani at different daily average temperatures.



***Source*:** Kobayashi, T., Ijiri, T., Mew, T. W., Maningas, G., & Hashiba, T. (1995).

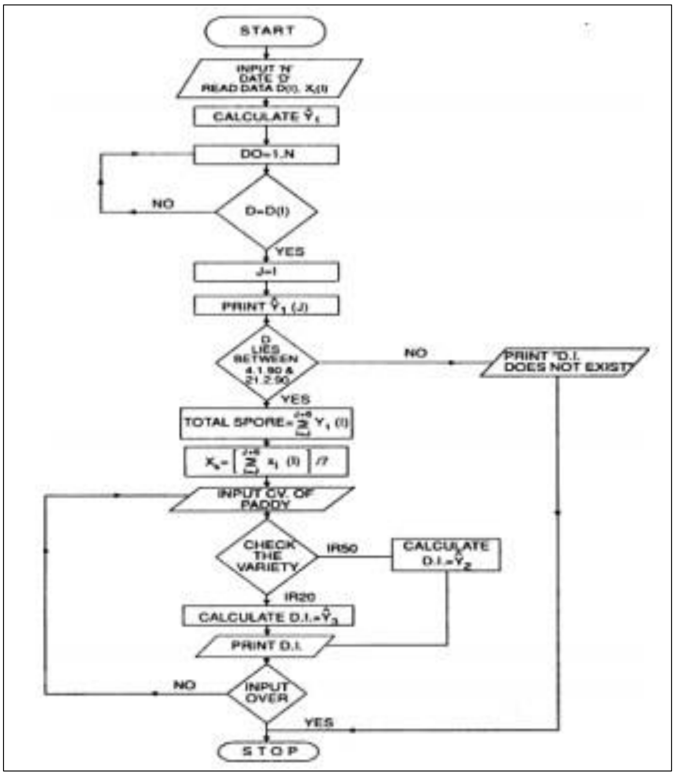
Fig 4: Flow chart of forecasting program for rice sheath blight disease.

BGRcast disease forecasting model for bacterial grain rot of rice, which is caused by ditions to epidemic development of BGR and forecasting risk of BGR development. Burkholderia glumae, was developed in this study. It determines daily conduciveness of weather con BGR model was developed collecting data from the field observations on disease incidence at Naju, Korea.

Epibla: EPIBLA (EPIdemiology of BLAst) is a digitally forecasting system modified to inspire the incidence and growth of rice leaf blast in the field. An accord-wise regressive analysis was used to evaluate the model for supreme fit to predict the atmospheric spores and disease advance on rice cultivars IR20 and IR50. There are three equations used to evaluate the quantity of blast spores and to assume disease prevalence. The estimated values were nearer to observed values. The partial regression coefficient advices that temperature and relative humidity affects spore dispersal consequently, number of spores, temperature (14-25 ˚C), relative humidity (73-100 percent), and amount of dew affects significantly of disease incidence. This model is developed in India by P. Krishan and K. Manibhushan Rao in 1991. It is an accordingly regression analysis to check this system for the best fit in predicting disease progress and atmospheric spores. It made a 7-day forecasts of disease progression in the tropical rice areas of India. EPIBLA was developed by following the several regression equations.

$$Y= \alpha + \beta1\ x1 + \beta2\ X2 + \ldots\ldots.. + \beta nXn$$

Where, Y, is either the number of spores/m3 of air or disease incidence, α, the intercept, β, the partial regression coefficients, and X, the predictor variables. While predicting the number of spores in the air, daily values of maximum relative humidity and maximum temperature served as predictors in the equations.



***Source*:** SINGH, O., BATHULA, J., SINGH, DK.

Fig 5: Epibla model for rice blast forecasting

Asset

The economic issue is one of reducing the cost of production by timely application of control measures, usually in the form of fungicides. This escape unavoidable wastage of fungicides as they are only enforced when required, usually at the opening of the epidemic.

safety is not about the crop. reducing possible on phytotoxic effects of pesticides; also, the environment - reducing exposure to non-target species, operators, and consumers. Some countries, particularly Scandinavia, have a target to reduce pesticide loading by 50%.

Since the foretelling involves ascertaining the conditions of an agro-climatic zone, it informs the growers regarding once the conditions area unit attending to be sufficiently favorable for economically necessary diseases therein zone. This helps growers apply infection management timely which leads to economic gain.

Forecasting informs the growers whether conditions do not seem to be favorable, and therefore the infection is unlikely to be intense enough. This helps growers to save lots of the expenditure in terms of your time, energy, and money by not applying avoidable management measures.

Forecasting helps growers to set up advance preventive measures against possible losses because of the prevalence of economically necessary severe diseases.

Government and alternative organizations initiate necessary steps for the timely stocking of chemicals, equipment, etc. after the area unit are timely warned of the possibility of pestilence by the forecastings.

However, there are several diseases within which reliable and early statements are helped the crop growers reducing losses from plant diseases to an excellent extent.

A prediction model depends on the communication with environmental condition at the time of executive and late-season disease severity could be used to help management decisions. Thus, if a sound for warming system is advanced, the disease could be managed by timely application result of the models enabling an analysis of the factor which governs disease epidemics as the model of control systems to reduce the yield losses. Some studies attempted the present case study on rice blast disease forecasting by following a new prediction approach, support vector machine and related its work with the exiting artificial neural network- based and multiple regression based prediction access. (Asibi, 2019) [2].

Future Aspects

Different modeling approaches *viz*. multiple correlations and neural networks have been following till date for predicting sickness in crop populations. However, due to their inability to predict worth of longer instruction times and unknown statistics points, that would like for exploiting new predicting software for higher understanding of plant-pathogen-environment relationships. Further, there's no online tool out there that might facilitate the plant researchers or farmers in a timely application of management measures. This paper introduces a brand-new prediction approach being supported. Support the vector machines for advancing climate-based predicting models of crop diseases.

Some case studies have shown that SVM is a advance then the present machine-learning techniques & traditional REG approaches in forecasting plant disease. SVM-based webserver have been developed for rice blast prediction. This can help the crop science society & farmers in their making process accordingly.

This paper introduces a replacement predicting methodology and techniques that support powerful machine learning technique. Support Vector Machines (SVM) originally developed by a company Vapnik and their coworkers at Bell Laboratories as an effective technique for general-purpose managed prediction. It has been observed within the past that this machine learning technique is incredibly effective within the classification of proteins particularly in discerning membrane proteins prediction of sub-cellular localization, solvent accessibility, CTL epitopes, protein-protein binding site, binding peptide binding macro-molecule structures, and organic phenomenon level. SVM equipes associate degree alternative or complement to this ANN and REG-based advances for model enhancement.

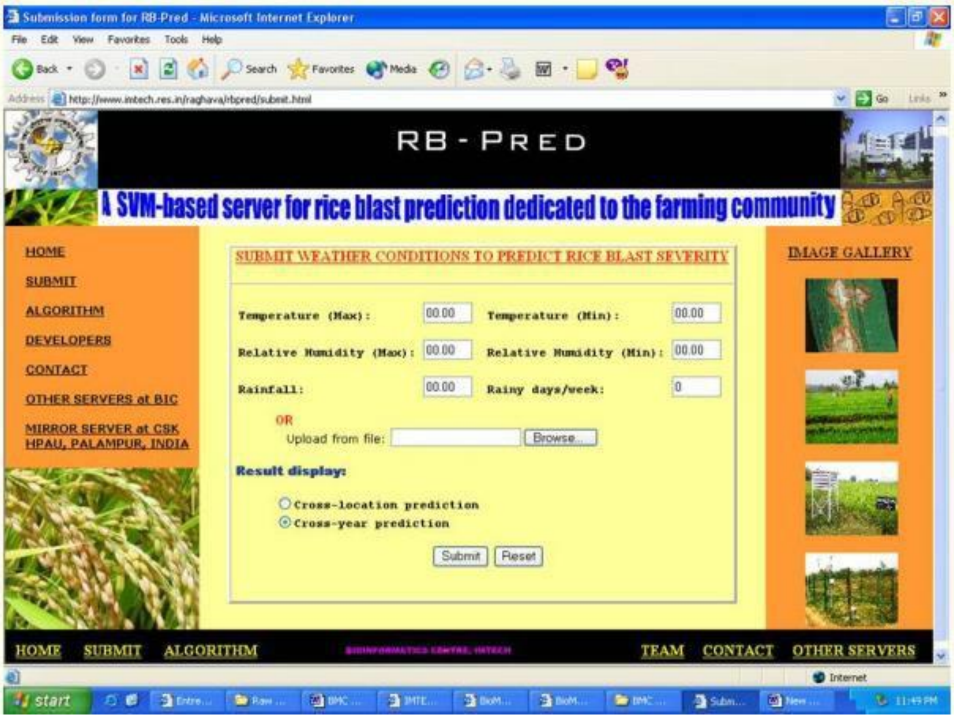
The SVM determines the way to label from a practice set of featured vectors, whose conventional outputs are already eminent. The proceeding enables a binary classification of SVM to outline a plane within the featured region, that optimally separates the training vectors of two categories. Once a replacement featured vector is delivered, its class is expected on the premise of that aspect of the plane it maps.

At the most effective of authors' data, the modern case study was aimed to administer the usefulness of “SVM models over the present artificial neutral network and conventional numerous regression models to forecast rice blast severity” based on predominant climatic conditions both within and between the locations/years, and also to evaluate the total risk of the blast disease at these field sites by using a set of weights from the practiced SVM models (Praneet, 2018) [13].

Developed Web Server

Rice farmers in most developing countries demand immediate results once disese problems are encounters A web based server, RB- Pred was modified to forecast the severity percent of leaf blast. Users just have to deliver the reported whether variables privailing in their areas *Viz,* maximum temperature, maximum relative humidity, minimum relative humidity, rainfall and rainy days week data in the submit from the server, based on the highest correlation coefficient and minimum percent mean absolute error, we have preferred the two models each for ‘cross location’ as well as for ‘cross year’ prediction. The serves is working well and will be favorable to the plant pathologist and farmer forecast the real time disease severity for their.

Previous attempts to describe the relationship between rice blast severity and environmental condition have been made in various countries. Through both the empirical and explanatory simulation models developed only through the conventional regression analysis *viz,* in Japan. Korea, chaina, india, Thailand, Taiwan and the Philipines. However, extremely limited use of these models has been implemented by farmers to manage rice blast because of two plausible reason, firstly growers- farmers tend to be risk- averse and are not properly convinced on the use of disease forecasting tools, and secondly the mathematical relationship between the environmental condition and the specific stages of rice blast infection cycle are not fully understood. This makes conventional modelling approaches such as multiple regression difficult.



Source: web-based server, RB-Pred

Year(s)	Location(s)		Multiple Regression (REG)			Artificial Neural Network (ANN)						Support Vector Machine (SVM)		
						BPNN			GRNN					
	Training Data	Test Data	r	r^2	%MAE	r	r^2	%MAE	r	r^2	%MAE	r	r^2	%MAE
2000	L-I, L-II, L-III, L-IV	L-V	0.62	0.38	75.12	0.51	0.26	51.94	0.62	0.38	37.83	0.62	0.38	37.42
	L-I, L-II, L-III, L-V	L-IV	0.59	0.35	99.77	0.69	0.48	72.75	0.60	0.36	41.39	0.69	0.48	39.41
	L-I, L-II, L-V, L-IV	L-III	0.57	0.33	39.20	0.60	0.36	49.47	0.75	0.56	40.35	0.84	0.71	23.71
	L-I, L-V, L-III, L-IV	L-II	0.63	0.40	62.92	0.78	0.61	26.60	0.89	0.79	25.81	0.94	0.88	17.29
	L-V, L-II, L-III, L-IV	L-I	0.44	0.19	58.01	0.48	0.23	57.62	0.51	0.26	55.62	0.54	0.29	50.88
2001	L-I, L-II, L-III, L-IV	L-V	0.39	0.15	89.27	0.66	0.44	59.17	0.95	0.90	95.08	0.98	0.96	66.40
	L-I, L-II, L-III, L-V	L-IV	0.78	0.61	59.77	0.79	0.62	57.34	0.89	0.79	33.11	0.95	0.90	24.16
	L-I, L-II, L-V, L-IV	L-III	-0.24	0.06	73.18	0.21	0.04	59.45	0.41	0.17	50.50	0.51	0.26	35.30
	L-I, L-V, L-III, L-IV	L-II	0.50	0.25	52.35	0.45	0.20	59.50	0.52	0.27	48.87	0.63	0.40	42.56
	L-V, L-II, L-III, L-IV	L-I	-0.27	0.07	115.20	0.38	0.14	96.66	0.34	0.12	94.98	0.41	0.17	76.22
2002	L-I, L-II, L-IV	L-V	0.51	0.26	94.75	0.86	0.74	84.29	0.93	0.87	82.64	0.82	0.67	36.09
	L-I, L-II, L-V	L-IV	-0.71	0.50	110.72	0.72	0.52	79.11	0.72	0.52	57.87	0.99	0.98	51.54
	L-I, L-V, L-IV	L-II	0.61	0.37	76.15	0.64	0.41	69.48	0.69	0.48	67.63	0.81	0.66	45.36
	L-V, L-II, L-IV	L-I	-0.15	0.02	108.31	-0.34	0.12	143.29	-0.30	0.09	127.32	0.12	0.01	95.39
2003	L-I, L-II, L-III, L-IV	L-V	0.46	0.21	67.92	0.50	0.25	53.61	0.63	0.40	49.30	0.86	0.74	42.93
	L-I, L-II, L-III, L-V	L-IV	0.14	0.02	74.96	0.46	0.21	65.17	0.51	0.26	59.29	0.86	0.74	41.80
	L-I, L-II, L-V, L-IV	L-III	0.53	0.28	68.09	0.59	0.35	58.59	0.87	0.76	49.57	0.88	0.77	19.76
	L-I, L-V, L-III, L-IV	L-II	0.69	0.48	69.78	0.70	0.49	61.70	0.72	0.52	58.39	0.78	0.61	53.17
	L-V, L-II, L-III, L-IV	L-I	0.57	0.33	53.05	0.65	0.42	51.09	0.69	0.48	49.85	0.70	0.49	49.18
2004	L-I, L-II, L-IV	L-V	0.18	0.03	90.55	0.63	0.40	61.81	0.73	0.53	41.01	0.83	0.69	38.86
	L-I, L-II, L-V	L-IV	0.68	0.46	78.63	0.72	0.52	45.20	0.76	0.58	37.10	0.86	0.74	31.67
	L-I, L-V, L-IV	L-II	0.39	0.15	89.98	0.10	0.01	65.18	0.44	0.19	51.82	0.69	0.48	46.54
	L-V, L-II, L-IV	L-I	0.47	0.22	54.88	0.43	0.19	69.34	0.67	0.45	67.79	0.74	0.55	40.70

Source: Kaundal, R., Kapoor, A. S., & Raghava, G. P. (2006) [5, 6]. Machine learning techniques in disease forecasting.

Fig 6: Contrast of a multiple regression (REG), generalized regression neural network (GRNN), backpropagation neural network (BPNN), and support vector machine (SVM) based forecast skill of rice blast severity is measured as coefficient of determination (r2), correlation coefficient (r), and percent mean absolute error (%MAE) of the realized value for 'cross- location' models over previous years.

Location(s)	Year (s)		Multiple Regression (REG)			Artificial Neural Network (ANN)						Support Vector Machine (SVM)		
						BPNN			GRNN					
	Training Data	Test Data	r	r^2	%MAE	r	r^2	%MAE	r	r^2	%MAE	r	r^2	%MAE
L – I	2000,01,02,03	2004	0.56	0.31	56.85	0.59	0.35	56.19	0.66	0.44	50.72	0.67	0.45	46.23
	2001,02,03,04	2000	0.36	0.13	60.37	0.50	0.25	58.90	0.63	0.40	40.86	0.75	0.56	38.07
	2000,02,03,04	2001	0.69	0.48	61.68	0.71	0.50	59.73	0.72	0.52	59.17	0.78	0.61	49.06
	2000,01,03,04	2002	0.17	0.03	85.70	0.17	0.03	77.18	0.35	0.12	75.97	0.54	0.29	67.35
	2000,01,02,04	2003	0.30	0.09	65.19	0.58	0.34	53.59	0.62	0.38	52.92	0.70	0.49	39.14
L – II	2000,01,02,03	2004	0.62	0.38	92.79	0.11	0.01	72.18	0.49	0.24	70.58	0.66	0.44	43.52
	2001,02,03,04	2000	0.58	0.34	45.04	0.78	0.61	44.29	0.93	0.87	40.15	0.93	0.87	25.41
	2000,02,03,04	2001	0.23	0.05	77.56	0.42	0.18	73.12	0.53	0.28	62.49	0.53	0.28	50.32
	2000,01,03,04	2002	0.48	0.23	51.76	0.56	0.32	48.09	0.76	0.58	41.03	0.79	0.62	40.13
	2000,01,02,04	2003	-0.10	0.01	99.31	0.20	0.04	60.62	0.22	0.05	56.81	0.60	0.36	45.54
L-III	2000,01	2003	0.50	0.25	52.72	0.68	0.46	36.30	0.82	0.67	29.97	0.84	0.71	20.27
	2001,03	2000	0.62	0.38	43.67	0.60	0.36	40.62	0.83	0.69	33.38	0.86	0.74	22.18
	2000,03	2001	0.14	0.02	71.93	0.58	0.34	38.30	0.63	0.40	35.93	0.65	0.42	35.10
L-IV	2000,01,02,03	2004	0.66	0.44	56.99	0.62	0.38	51.72	0.78	0.61	49.62	0.84	0.71	47.49
	2001,02,03,04	2000	0.55	0.30	53.03	0.68	0.46	45.99	0.72	0.52	43.31	0.77	0.59	41.90
	2000,02,03,04	2001	0.89	0.79	68.55	0.89	0.79	65.23	0.90	0.81	30.75	0.97	0.94	29.90
	2000,01,03,04	2002	0.84	0.71	91.18	0.90	0.81	23.93	0.94	0.88	20.95	0.96	0.92	14.79
	2000,01,02,04	2003	0.48	0.23	71.71	0.56	0.31	67.39	0.58	0.34	62.60	0.66	0.44	40.39
L-V	2000,01,02,03	2004	0.38	0.14	78.13	0.64	0.41	62.55	0.66	0.44	56.82	0.80	0.64	50.22
	2001,02,03,04	2000	0.67	0.45	55.71	0.71	0.51	38.99	0.73	0.53	32.09	0.98	0.96	15.23
	2000,02,03,04	2001	0.78	0.61	72.13	0.83	0.69	52.07	0.90	0.81	50.56	0.93	0.87	21.18
	2000,01,03,04	2002	0.53	0.28	56.44	0.86	0.74	51.91	0.87	0.76	46.30	0.87	0.76	35.28
	2000,01,02,04	2003	0.61	0.37	54.91	0.61	0.37	50.26	0.62	0.38	48.17	0.65	0.42	46.17

Source: Kaundal, R., Kapoor, A. S., & Raghava, G. P. (2006) [5, 6]. Machine learning techniques in disease forecasting.

Fig 7: Contrast of a multiple regression (REG), generalized regression neural network(GRNN), backpropagation neural network(BPNN), and support vector machine(SVM) based forecast accuracy on rice blast severity is measured as correlation coefficient (r), coefficient of determination (r2) and percent mean absolute error (%MAE) of realized value for 'cross-year' models over numerous positions.

Model(s)	Multiple Regression (REG)			Artificial Neural Network (ANN)						Support Vector Machine (SVM)		
				BPNN			GRNN					
	r	r^2	%MAE	r	r^2	%MAE	r	r^2	%MAE	r	r^2	%MAE
Cross-location models												
2000	0.57	0.33	67.01	0.61	0.39	51.68	0.67	0.47	40.20	0.73	0.55	33.74
2001	0.44	0.23	77.95	0.50	0.29	66.42	0.62	0.45	64.51	0.70	0.54	48.93
2002	0.50	0.29	97.48	0.64	0.45	94.04	0.66	0.49	83.87	0.69	0.58	57.09
2003	0.48	0.26	66.76	0.58	0.34	58.03	0.68	0.48	53.28	0.82	0.67	41.37
2004	0.43	0.22	78.51	0.47	0.28	60.38	0.65	0.44	49.43	0.78	0.62	39.44
Average	**0.48**	**0.27**	**77.54**	**0.56**	**0.35**	**66.11**	**0.66**	**0.47**	**58.26**	**0.74**	**0.59**	**44.12**
Cross-year models												
Location-I	0.42	0.21	65.96	0.51	0.29	61.12	0.60	0.37	55.93	0.69	0.48	47.97
Location-II	0.40	0.20	73.29	0.41	0.23	59.66	0.59	0.40	54.21	0.70	0.51	40.98
Location-III	0.42	0.22	56.11	0.62	0.39	38.41	0.76	0.59	33.10	0.78	0.62	25.85
Location-IV	0.68	0.49	68.29	0.73	0.55	50.85	0.78	0.63	41.44	0.85	0.73	34.90
Location-V	0.59	0.37	63.46	0.73	0.54	51.15	0.76	0.58	46.79	0.84	0.72	33.62
Average	**0.50**	**0.30**	**65.42**	**0.60**	**0.40**	**52.24**	**0.70**	**0.51**	**46.30**	**0.77**	**0.61**	**36.66**

Source: Kaundal, R., Kapoor, A. S., & Raghava, G. P. (2006) [5, 6]. Machine learning techniques in disease forecasting.

Fig 8: Overall contrast of multiple regression (REG), generalized regression neural network (GRNN), back-propagation neural network (BPNN), and support vector machine (SVM) based forecast accuracy on rice blast severity is measured as average correlation coefficient (r), coefficient of determination (r2) and percent mean absolute error (%MAE) of realized value for 'cross-location' and 'cross-year' models.

Best predictor variables

For 'cross-location' acceptance, the best SVM model was examined during 2001 with location- V as test data (farmers' fields, Pharer) with the higher correlation coefficient of 0.98 and percent mean absolute error of 66.40. The performance of this model was over-tested by ignore each weather variable at a time by repeated training and testing. The results admit that rainfall was most dominant in predicting the disease followed by rainy days/week, minimum relative humidity, maximum relative humidity, minimum temperature and maximum temperature (Kaundal, R., Kapoor, A. S., & Raghava, G. P Fig 4). alike, for 'cross-year' models, the best SVM model was observed at location-V (farmers' fields, Pharer)

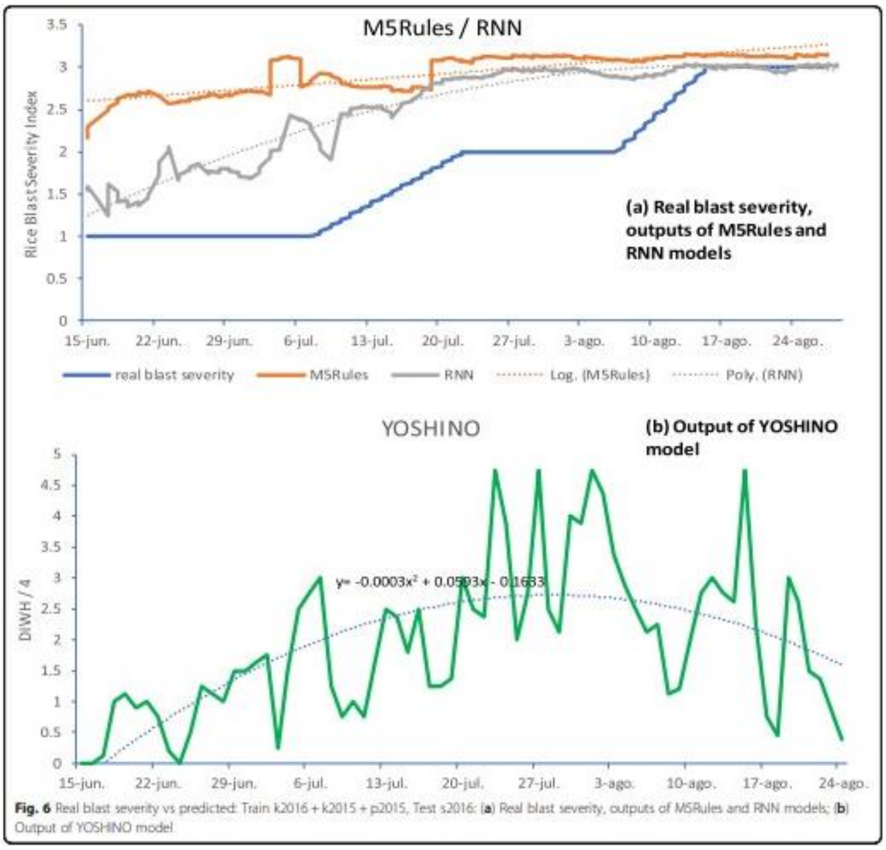
Again, rainfall was found to be the best predictor variable, as tested data with the year 2000 highest correlation coefficient of 0.98 and least present means an absolute error of 15.23. However, the second most dominant variable was found to be minimum relative humidity followed by maximum relative humidity, minimum temperature, maximum temperature, and rainy days/week. Elaborate, Rainfall had been seen to be the best predictor among the weather variables compared by relative humidity and rainy days week. The temperature was started to have least effect on disease improvement (Nayak, 2018) [11].

Finally, among four approaches REG, BPNN, GRNN, and SVM, the best prediction model has been selected. These are based on the maximum coefficient of determination and least percent mean absolute error values. then plotting the observed and predicted mean disease severity, after that comparison of two model cross year as well as cross location on their prediction accuracy. Within the cross-year models, best prediction accuracy was observed for location-IV (Rice Research Station, Malan) and for location-v (farmers' fields, Pharer). moreover, best testing was examined with the year 2000 data at all the locations except for location-IV (RRS, Malan) where best acceptance was observed with 2001 data. In case of cross-location models, best prediction efficiency was observed for 2003- and 2004-years data (Figure 6, 7)

Machine learning versus process-based models: Predicting rice blast disease

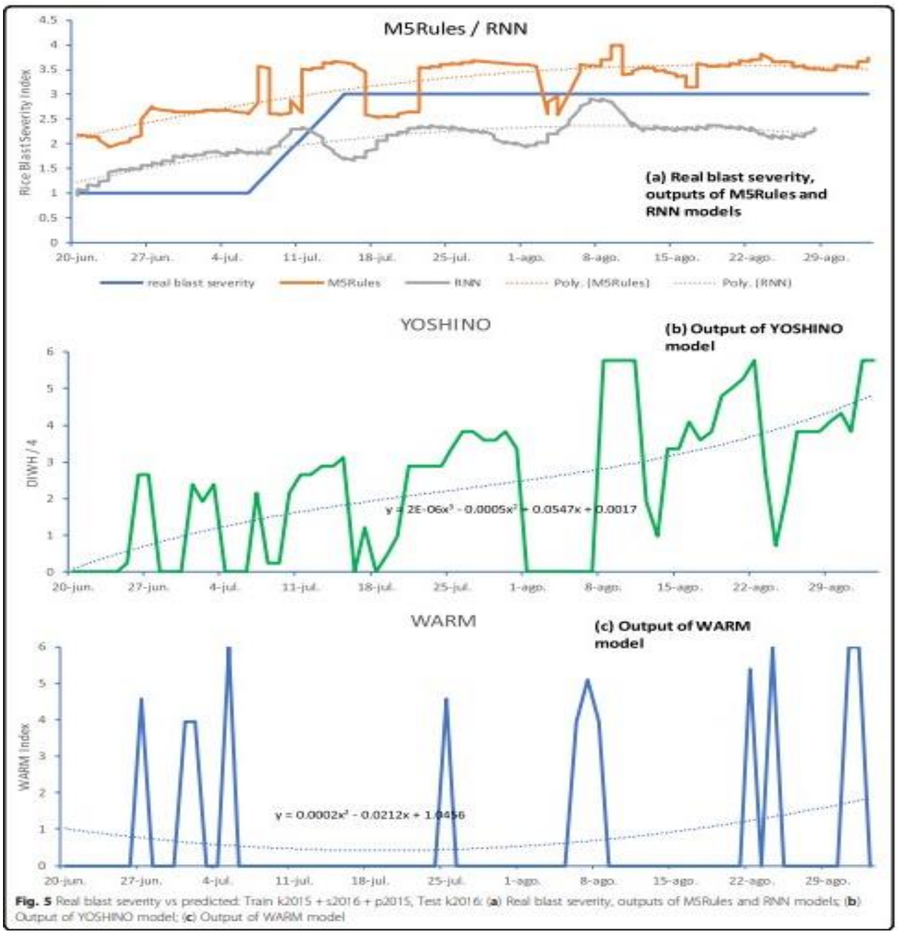
From the study, Forecasting techniques could be used to identify that which years are conductive and whether fungicide application would be cost effective or risky under those conditions. We compromise four models for predicting rice blast disease, two working process based models (Yashino and WARM) and two approaches based on machine information algorithms (M5 Rules and RNN). Results apparently showed that the models accomplished in providing a warning of rice blast onset and presence, thus representing applicable solution for preventive remedial action targeting the mitigation of yield losses and the contraction of fungicide use. All methods gave important "signals" during the "early warning" period, with a similar level of achievement. Since most of the available studies are finite to the analysis of the relationship between the model outputs and the rate of rice blast. Conclution also showed that machine learning models approximated the achievement of two process based models else for years in operational. (Nettleton, 2019) [12].

All the approaches under evaluation, i.e., Yoshino, WARM and the two machine learning approaches (M5Rules and LSTM RNNs), succeeded in providing warnings for the onset and presence of rice blast early enough to allow farmers to take necessary measures. This can be seen from Figs. 9 and 10, where the output of all models triggers before the blast severity actually starts.



Source: Nettleton, D. F., Katsantonis,D., Kalaitzidis, A., Sarafijanovic-Djukic, N., Puigdollers, P., & Confalonieri, R. (2019) [12].

Fig 9: Real blast severity, output of M5Rules & RNN models, (b) output of YOSHINO model © output of WARM model.



Source: Nettleton, D. F., Katsantonis, D., Kalaitzidis, A., Sarafijanovic-Djukic, N., Puigdollers, P., & Confalonieri, R. (2019) [12].

Fig 10: (a) Real blastseverity, outputs of M5Rules and RNN models; (b) output of YOSHINO model

Limitations:

Cultivar will be a fantastic way for this disease control also be easy then applying forecasting, how its time consuming and a longtime process. Forecasting systems are a vast programmed itself. for achieve success on this model development one must conquer total epidemic concept of working topics (Agbowuro, 2020) [1]. Forecasting is not specific solution for any epidemic diseases but to get low yield loss as compared to normal yield loss. Which avoided by the farmers. Famous forecasting models like EPIRISE & EPIBLAST both are needed to revise in some cases improvement for EPIRICE suggested three specific areas, a) the treatment of spatial structure of disease epidemics. B) the handling of epidemiological processes in vector borne diseases. C) the limited published disease progress curves and basic information. For the case of EPIBLAST causes rice blast in Thailand scientist observed some fluctuations, particularly when weather would be changing rapidly. Disease forecasting systems are based on assumptions concerning the particular pathogens interactions with the host and the environment, the "disease triangle" of "infectious pathogen," "vulnerable host" and "agreeable environmental condition. "There is no broad way to organize all the disease models and modeling start to deal with in a certain way used in agriculture. Researchers have initially indicated that most epidemic models are either analytic or simulations. Such problems are generally,

Model inputs have high degree of ambiguity.

Nonlinear relationships between climatic variables and epidemic parameters. Potential for adaptations of plants and pathogens.

Conclusion

Inquiry of published rice blast forecast models has provided broad awareness on rice blast forecasting. Weather variables, being air temperature, relative humidity, spore dissemination and leaf wetness are among the most demanding model inputs since these plays' vital role in P.oryzae pathogenesis and rice blast evolution. the eventual goal of foretelling is to predict not only the time of apparent disease explosion but also the load of disease incidence at a sure point.

References

1. Agbowuro GO *et al*. "Rice Blast Disease (Magnaporthe oryzae): A Menace to Rice Production and Humanity." International Journal of Pathogen Research 2020, 32-39.
2. Asibi, Aziiba Emmanuel, Qiang Chai, Jeffrey A. Coulter. "Rice blast: A disease with implications for global food security." *Agronomy* 2019;9(8):451.
3. Hashiba T, Ijiri T. Estimation of yield loss and computerized forecasting system (BLIGHTAS) for rice sheath blight disease. Trop. Agric. Res. Ser 1989;22:163-173.
4. Katsantonis D, Kadoglidou K, Dramalis C, Puigdollers P. Rice blast forecasting models and their practical value: a review. Phytopathologia Mediterranea, 2017, 187-216.
5. Kaundal R, Kapoor AS, Raghava GP. Machine learning techniques in disease forecasting: a case study on rice blast prediction. BMC bioinformatics 2006;7(1):1-16.
6. Kaundal R, Kapoor AS, Raghava GP. Machine learning techniques in disease forecasting: a case study on rice blast prediction. BMC bioinformatics 2006;*7*(1):1-16.

7. Kim CK. Disease forecasting: past and future in special reference to rice leaf blast. Korean Journal Plant Pathology 1987;3(4):304-312.
8. Kim CK, Kim CH. The rice leaf blast simulation model EPIBLAST. In Systems approaches for agricultural development Springer, Dordrecht 1993, 309-321.
9. Kobayashi T, Ijiri T, Mew TW, Maningas G, Hashiba T. Computerized forecasting system (BLIGHTASIRRI) for rice sheath blight disease in the Philippines. Japanese Journal of Phytopathology 1995;61(6):562-568.
10. Lee YH, Ko SJ, Cha KH, Park EW. BGRcast: a disease forecast model to support decision-making for chemical sprays to control bacterial grain rot of rice. The plant pathology journal 2015;31(4):350.
11. Nayak, Parsuram. *et al*. Application of statistical tools for data analysis and interpretation in rice plant pathology. Rice Science 2018;25(1):1-18.
12. Nettleton, David F. *et al*. Predicting rice blast disease: machine learning versus process-based models. BMC bioinformatics 2019;20(1):1-16.
13. Praneet C, Sunita C. Role of modelling in plant disease management. International Journal of Plant Protection, 2018;11(1):124-134.
14. Sella, Luca, *et al*. Sustainable Methods to Control Pyricularia oryzae, the Causal Agent of Rice Blast Disease. Innovations in Land, Water and Energy for Vietnam’s Sustainable Development. Springer, Cham, 2021, 67-82.
15. Singh O, Bathula J, Singh DK. Rice blast modeling and forecasting. Int J Chem Stud 2019;7(6):2788-2799.
16. Srivastava, Deepti *et al*. "Current status of conventional and molecular interventions for blast resistance in rice." Rice Science 2017;24(6):299-321.