R.Beulah, et. al. International Journal of Engineering Research and Applications
www.ijera.com
ISSN: 2248-9622, Vol. 10, Issue 9, (Series-I) September 2020, pp. 38-45

RESEARCH ARTICLE OPEN ACCESS

Prediction of Pesticides Used For Crop Production on the Environment Using Fuzzy Random Forest Classifier

R.Beulah*, M.Ravichandran**
**(Department of Computer Science, Sri Ramakrishna Mission Vidyalaya college of Arts and Science, Coimbatore-20*
*** (Department of computer Science, Sri Ramakrishna Mission Vidyalaya college of Arts and Science, Coimbatore-20*

ABSTRACT
One of the problems that Indian farmers face today is how to use pesticides in the correct way , i.e. some pesticides function properly in some lands. Recent research findings on the presence of pesticide particles in packaged water are classic cases of the nature and magnitude of the problem. Simultaneously, increased use of chemical pesticides has resulted in environmental pollution and there are many long-term implications for society. Knowingly or unknowingly, farmers are now being accused of using agrochemicals indiscriminately and unnecessarily to make the situation worse, not only in India, but also in other parts of the world. Suppose that if the chemical worked perfectly in Chennai, then the manufacturers in Chennai developed pesticides that helped their soil conditions. However, if similar pesticides are used in Nellore, they do not work due to specific soil conditions. Farmers might also lose a ton of cash and commit suicides together. In order to resolve the above problem, a multi-classifier method using a fuzzy random forest classifier is implemented to predict pesticide utilization for crop production. Experimental works demonstrates the superiority of the proposed algorithm as it has outperformed the well-established benchmark algorithm such as Naïve Bayes Classifier, Support Vector Machine (SVM), Multiple Linear Regression (MLR), Neural Network Classifier (NN) and Bayesian Network (BN) in terms of precision, recall, F-measure and accuracy.

Keywords – Fuzzy random forest classifier, Naïve Bayes Classifier, Support Vector Machine, Multiple Linear Regression, Neural Network Classifier and Bayesian Network.

Date of Submission: 20-08-2020 Date of Acceptance: 06-09-2020

I. INTRODUCTION

In India, yield per hectare of crops is typically poor compared to international standards. The main reason for this is inadequate water management, a lack of soil nutrients leading to plant diseases and an increasing number of pests destroying yields. It is therefore more important to forecast the use of pesticides to avoid pest crops. Today, modern people are not aware of growing crops at the right time and in the right place [1]. Thanks to these cultivation techniques, seasonal climatic constraints are also being changed against fundamental assets such as soil, water and air, which lead to food anxiety. Through evaluating all these problems and concerns, such as environment, temperature and a variety of variables, there is no proper solution and technologies to solve the problem we face. In India, there are many ways to improve agricultural economic development. There are many ways of growing and enhancing crop yields and crop quality [2].

The use of pesticides in agriculture is increasingly reported to cause environmental disturbances and health hazards, particularly for people directly exposed to them. In temperate climates, agriculture is occupied by intensive farming systems with a high level of specialized crop production and a high level of dependence on pesticides and mineral fertilizers [3]. While several research have concentrated on evaluating the feasibility of traditional and creative farming methods, if fewer pesticides will be as effective and competitive as current agricultural practices remain contentious. Some studies indicate that pesticides are essential for the control of pests and for ensuring a high level of food safety, and that a reduction in pesticide use can lead to a dramatic loss of yield and profit [4]. Those certain experts contend that pesticides endanger sustainable agriculture and that a significant reduction in pesticides use can be reconciled with high levels of performance, which include crop productivity and farm profit margins.

Data mining that is often useful to forecast crop production. In general, data mining is the process of analyzing and summarizing data into useful information from different perspectives. Data

mining software is an analysis tool for analysing, categorizing and summarizing data from many different dimensions or angles [5]. Technically the mining of data is the process by which tens of fields in large relational databases find correlations or patterns. Information can be provided by patterns, associations or relations between all these data. The knowledge on history and future trends can be converted into information. Detailed knowledge on crop production, for instance, will help farmers recognise and avoid crop losses in future [6]. The prediction of crop yields is a major problem in agriculture. Each farmer is constantly trying to know how much of his expectations will yield. In the past, a study of farmers' previous experience in a given crop has estimated the yield preview. The agricultural output depends primarily on weather conditions, pests and crop planning. Precise knowledge on crop yield history and pesticide prediction is relevant in decision taking in relation to management of agricultural risk.

A Naïve Bayes algorithm [7], Support Vector Machine (SVM) [8], Multiple Linear Regression (MLP) [9], Neural Network [10] and Bayesian Network [11] was used in an appropriate model to predict the pests or diseases of crops. While these approaches successfully forecast crop pests or diseases, it did not provide the infected crops with knowledge regarding pesticides. A five-stage roadmap [12] was used to model the agricultural system's effects on pests and diseases. Yet in the field of forecasting pesticide use for crop growth there is no work being conducted. Therefore, the key goal in this research work is to implement a multiple classifier network of fuzzy random forest classifiers to forecast the usage of pesticides in crop growth. Fuzzy random forest is a fuzzy decision trees with ensemble learning with random forest. The first approach is to integrate the knowledge from the various leaves reached in each tree to get each specific tree's decision and then use the same or another hybrid process to produce the Fuzzy random forest ensemble's global preference. The second approach is to integrate the knowledge from all the leaves reached from all trees to produce the Fuzzy random forest ensemble global judgment. Based on these ambiguous random forest techniques the usage of pesticides for growth is expected.

The rest of the paper is structured as follows: section 2 deals with the related work on pesticide prediction and section 3 describe the background methods and section 4 describes the proposed methodology. The section 4 explains about the results and discussion. Finally conclusion with future work is described in section 5.

II. RELATED WORK

In [13] the framework that operates on pre-processing proposed function extraction of leaf images from plant village dataset accompanied by convolution of neural network for disease classification and suggestion of Pesticides utilizing Tensor flow technology. A hybrid constructional and methodological solution suggested in [14] is including variety introduction, pesticide & fertilizer control, organized cropping, rainwater harvesting, successful irrigation techniques etc. In [15], discovered over time that pesticides affect human health and the climate. Although many farmers are conscious of the dangers of overuse of agricultural pesticides, they nevertheless use them to allow higher returns and increase financial gain or reduce financial losses.

Attempts to determine the vulnerability of public non-agricultural areas to pesticide drift and investigate the root causes in [16] seek. In addition, this analysis indicates that pesticides migrate through playgrounds from nearby farm areas, and that higher percentages of apple orchards in the area, drought and windy conditions during wind-still cycles enhance the pollution of such sites by pesticides. In [17], the object of which is to address pesticides, their forms, their utility and their related environmental concerns. Contamination resulting from overuse of pesticides and the long-term environmental impact of pesticides are also discussed.

In [18] studied, it brings together information and empirical studies on the control of pesticide products, restrictions on pesticides, residues of pesticides in food and their safety impact on humans. Also, connect up activities such as good agricultural practices (GAP) and numerous food protection programs to encourage sustainable practices in food production. In [19] released review on the usage of agricultural pesticides in Iran with the goal of defining pesticide items with potential to cause acute or chronic human health hazards. It also lays out a framework for future analyses and pattern assessments.

III. BACKGROUND METHODS

Naïve Bayes Classifier: A classifier Naive Bayes is a model of probabilistic machine learning which is used for classification tasks. The classification's main thrust is focused on the Bayes theorem [7].

$$P(C \mid D)=(P(D \mid C)P(C))/P(D)$$

Using Bayes theorem, provided that D has happened, one will consider the likelihood of C occurring. Here, evidence is D, and inference is C.

Support vector Machine: Support Vector Machines is a classification technique that

distinguishes data values by hyper plane creation [8]. Hyper planes may be of various shapes based on data spread, and those points are included for classification which help distinguish between the groups. Support Vector Machine deployment presented as follows:

1. Load the data sets and the clean values, if there is no value for a specific function in a list, overwrite the dataset with the median value of the list.
2. Break the data collection into the train and check at a ratio of 60:40.
3. Choosing the kernel function as the vector kernel function or the radial basis unit.
4. Apply SVM by first constructing a hyperplane with the aid of a test data collection.
5. Train data is obtained and the kernel feature is added.
6. Apply the test data collection to the trained model.
7. The configuration uses a hyperplane which is equivalent to either the class of cardiac disease (yes/1) or the class of cardiac disease (no/0).

Multiple linear regression (MLR): MLR is also known simply as multiple regression, a statistical technique that uses several explanatory variables to predict the outcome of the response variable. The purpose of multiple linear regression (MLR) is to model the causal relationship between the explanation (independent) variable and the answer (dependent) variable [9].

Neural Network Classifier: Neural nets are inspired by the process of learning that occurs in human brains. This consists of an artificial network of features, called parameters, which allows the machine to learn and fine-tune itself by processing new data. Each parameter, occasionally did refer to as neurons, is a function that produces output after receiving one or more inputs. Then these outputs are transferred to the next neuron layer, which uses them as inputs to its own functions and produces additional output. Those outputs will then be transferred to the next neural layer and will proceed until any neuronal layer has been taken into account and the terminal neurons have been generated. The final outcome for model [10] is then given by certain terminal neurons.

Bayesian Network Classifier: A Bayesian network describes the cumulative distribution of the likelihood of a random collection of variables, which could have a common source. The network consists of random variables, edges between pairs of nodes that represent the causal relationship of these nodes and a conditional distribution of probability in each node. The key aim of the approach is to model, after finding new data, the resulting conditions likelihood distribution of outcome variables (often causal) [11].

IV. PROPOSED METHODOLOGY

4.1 Units for Magentic Properties Algorithm of Fuzzy Decision Tree

Input: The selected crop and pesticide dataset D, maximal number of splits N_s,the set of partition points p, membership function $\mathcal{F}$, the metric of choosing the bset node, the largest error gain ER_G, n the number of instances in the dataset, the selected features of ith sub-FuzzyTree $Feature_i$;

Output: FDT results $FuzzyTree$

1. Initialize the $FuzzyTree = null, ER_G = 0, \mathcal{F} = Null$;
2. $Fuzzification$:
3. For $i = 0; i \neq N_s - 1; i = i + 1$ do $p_i \rightarrow$searching for good partitions:constructing Gaussian membership function $\mathcal{F}(D)$
4. End for building fuzzy decision tree (FDT)
5. $FuzzyTree = Procedure\ call\ (D, N_s, p_i, \mathcal{F})$
6. Procedure call $FuzzyTree()$
7. Select the best feature with most massive ER_G
8. For $i = 0; i \neq n - 1; i = i + 1$ do $ER_G \rightarrow$computing the impurity ratio(chosen p_i, $\mathcal{F}(i) \rightarrow \mathcal{F}(D)$)
9. If $ER_{G_i} > the\ bset\ ER_G$ then $the\ bset\ ER_G = ER_{G_i}; the\ bset\ node = i$
10. End if and end for
11. For $i = 0; i \neq N_s - 1; i = i + 1$ do $FuzzyTree_i = Null; D_i = subset(D, Feature_i); p_i = ubset(D, Feature_i); \mathcal{F}_i = subset(\mathcal{F}, Feature_i); FuzzyTree_i =$
12. $method\ of\ buildtree(D_i, N_s, p_i, \mathcal{F}_i)$
13. Do step 1 to Terminal conditions $if\ D$ is pure (only one possible label exixts for the set D) or satisfies other condition then
14. Terminate and output ($FuzzyTree$)

End of all for and restore $FuzzyTree$

This section investigates the problem of the use of pesticides, a key research direction for identifying and predicting crop yields using pesticide. Numerous researchers use models to detect hidden label information to predict the use of pesticides (positive or negative credit). When coping with uncertain results, the fuzzy logic is resilient and

thus benefits the classification and prevision problem. The application of fluid logic depends on the data characteristics and the aims in an optimal way, and finding such a way is extremely difficult. Therefore, this research suggests a general model of the membership of the Fuzzy Decision Making Framework for the Fuzzy Random Forest System. In order to classify the usage of the pesticide with almost ideal fuzzy sets, the suggested approaches should be used. First, in the section selecting partitioning points and defining participant functionalities, a dynamic decision tree will be generated with some tacit simple assumptions. The methodology proposed then extends the random forest. The overall diagram of pesticide usage prediction is illustrated in Figure 1.

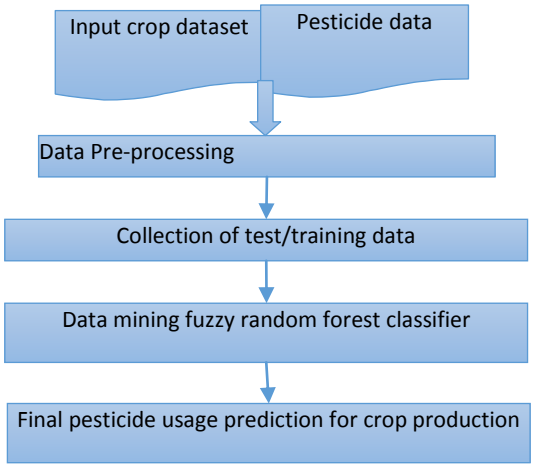

Fig.1. The Overall Diagram of Pesticide Usage Prediction

4.2 Fuzzy Decision Tree Model

This section explains the analysis of a Fuzzy Decision Tree (FDT). Let us first take the steps needed to build a normal, furious decision-making tree. Following are the fundamental steps to build a normal FDT:

1. Raise the initial (pesticide crop production) dataset;
2. Choose the metric to pick a feature;
3. To build a fuzzy decision tree, using recursive function;
4. Classify the developed fuzzy decision tree as new instances

The following four issues should be considered before the generation of the fuzzy decision tree:

- Identifying correct points for partitioning;
- identify strong principles for membership (build good membership functions);
- In any recursive step, select the best node (choose the right metric);
- After the furious decision tree has been made, measure the final risk estimate.

As can be seen from the above four issues, a membership feature is developed up in order to answer the first and second concerns concerning the hunt for partitioning points and the flush-mounting of the initial data set later. This method adopted the metric for selecting error-related functions, rather than a metric for information. Therefore the Gaussian membership will create the FDT and pick the calculation and accomplish the third point by choosing an error-related function. Then, the Gaussian membership function-based FDT can be generated as the steps of 4.1.

4.3 Fuzzy random forest

This section provides an extension from Fuzzy tree of decsion to Fuzzy Random forest. This section is for algorithm completion and a case study will be offered in the experimental portion. In addition, the architecture of the FuzzyTree can be extended to several other random forest algorithms as its key contributions concentrate on how to select good partitioning points and how to create a more robust membership function. There are some common procedures for building a bubbling random forest like the following:

- Fuzzify core datasets of crop and pesticide;
- Defines the number of fuzzy decision trees;
- Create vaguely random forest with various vaguely-decided trees;
- Defuzzify the test for labeling.

After that, by the similar procedure of building our Gaussian membership function-based fuzzy decision tree, we build the Gaussian membership function-based random forest. Our Gaussian Membership feature must perform the phase of fuzzifying the initial datasets. To be more precise, look for strong partitioning points just to have rule-based linear membership structure with the Gaussian membership and nonlinear membership function. Two separate types of rule-based Fuzzy random forest with linear and nonlinear membership structure of the Gaussian membership. Assume the number of Fuzzy Decision trees in this section for a random forest such as N_t. Formerly, by building $N_t$fuzzy decision trees separately, can build fuzzy random forest.

Create a Fuzzy Random Forest centered on our Gauussian membership feature in the table 2 method. This algorithm 's input is dataset D, and our fuzzy random forest 's outputs are a fuzzy random forest Fuzzy Random Forest, membership function $\mathcal{F}$, and then the set of partitioning points p. Then initialize as Null the fuzzy random forest FuzzyRandomForest and then it's the phase of fuzzy. Next, the primary procedure of building a Fuzzy

Random Forest is how to generate a Random Forest is the process of calling Algorithm 1 to obtain the FDT Fuzzy Tree and predicting the final use of pesticides. After that is the steps of combining and defuzzification to build a bubbling random forest. Finally returns the function-based fuzzy random forest Fuzzy Random Forest back to our Gaussian membership.

Defuzzification step: In this final stage, the calculated quantity of pesticides to be added to the crop will be transformed in crisp logic (digital meaning) from its fuzzy value (language term) to its counterpart. For any specified inputs, if only one fuzzy rule in the inference engine has been enabled, the output would only be allocated one fuzzy state with a special meaning between zero and one. To define the digital output value, it will suffice to apply this last fuzzy value to its appropriate fuzzy set in the triangular membership function. For other situations, if any inputs are regarded as (Low Medium, Medium High, or More High), two conditional rules may be triggered in the inference system. In the specific analysis the monitored production is known to be the use of pesticide values.

Algorithm of Fuzzy Random Forest

Input: the input crop pesticide dataset D,

Output: $FuzzyRandomForest$, membership function $\mathcal{F}$ and the set of partitioning point p

1. Initialization $FuzzyRandomForest = null$;
2. Fuzzification:
3. For $i = 0; i \neq N_s - 1; i = i + 1$ do

$p_i \rightarrow$searching for good partitions:constructing Gaussian membership function $\mathcal{F}(D)$

4. End for
5. Procedure of generating random forest
6. For $N_{t_i} = 0; i \neq N_{t_i} - 1; N_{t_i} = N_{t_i} + 1$ do
7. $FuzzyTree = Null; D_{subset} =$subset $(D,$ the selected features $Feature_i)$
8. $Buliding\ FDT\ using\ Algorithm\ 1$
9. $FuzzyRandomForest += FuzzyTree;$
10. $End\ for$
11. Return $FuzzyRandomForest$

V. RESULTS AND DISCUSSION

This section presents the performance of the fuzzy random forest (FRF) classifier method on three experiments using Pesticides usage for crop production dataset. The output of the FRF is compared with the existing methods such as Naïve Bayes Classifier, Support Vector Machine (SVM), Multiple Linear Regression (MLR), Neural Network Classifier (NN) and Bayesian Network (BN) Classifier with the performance metrics of precision, recall, f-measure, and accuracy. If the sample is positive and it is classified by ISVM as positive, i.e., correctly classified positive sample, it is counted as a true positive (TP); if it is classified as negative, it is considered as a false negative (FN). If the sample is negative and it is classified as negative it is considered as true negative (TN); if it is classified as positive, it is counted as false positive (FP).

Precision: It represents the proportion of positive samples properly classified as the total number of positive samples predicted, as indicated eq.(1):

$$Precision = \frac{TP}{FP + TP} \tag{1}$$

Recall: A classifier's recall represents the positive samples correctly classified to the total number of positive samples, and is estimated as follows:

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Receiver Operating Characteristic (ROC): The relation between clinical sensitivity and specificities of any possible cut off is illustrated by this curve. The ROC curve is a graph with:

The x-axis showing 1 – specificity $\rightarrow$ false positive fraction $\Rightarrow$FP/(FP+TN))

The y-axis showing sensitivity $\rightarrow$true positive fraction $\Rightarrow$TP/(TP+FN)).

Accuracy: It is one of the most commonly used measures for the classification performance, and it is defined as a ratio between the correctly classified samples to the total number of samples as follows:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

F-measure: F-measure is the weighted Precise and Recall average. So this score takes into account both false positives and false negatives. It's not as easy to understand intuitively as accuracy, but F-measure is usually more useful than accuracy, especially if you have an uneven class distribution.

$$F - measure = 2 * \frac{(Recall * Precision)}{(Recall + Precision)} \tag{4}$$

The numerical results of FRF, Naïve Bayes, SVM, MLR, (NN) and BN Classifier are given in Table 1.

TABLE 1. The numerical results of FRF, Naïve Bayes, SVM, MLR, (NN) and BN Classifier

Methods	Accuracy	Precision	Recall	F-measure
NaiveBayes	0.9125	0.8700	0.8723	0.8711
SVM	0.8875	0.8842	0.8821	0.8832
MLR	0.8950	0.8938	0.8922	0.8930
NN	0.9000	0.9000	0.8950	0.8975
BN	0.8750	0.9012	0.9054	0.9033
FRF	0.9250	0.9118	0.9167	0.9142

5.1 Precision Rate comparison

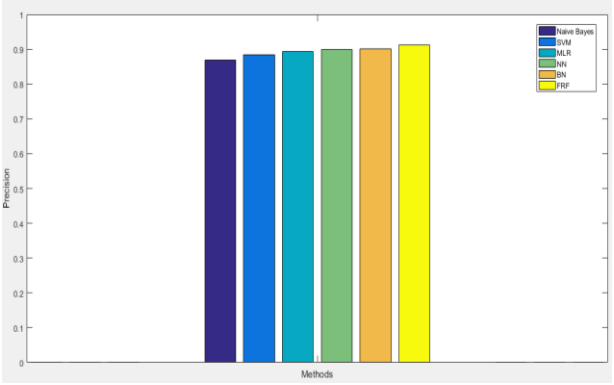

Fig.2. Precision comparison

From the above Figure 2, the graph explains that the precision comparison for the pesticide usage prediction. The methods are executed such as FRF, Naïve Bayes, SVM, MLR, (NN) and BN Classifier. When number of data increased according with the precision value is increased. From this graph, it is learnt that the proposed FRF provides higher precision rate of 0.9118 than the previous methods such as Naïve Bayes, SVM, MLR, (NN) and BN attains precision rate of 0.8700, 0.8842, 0.8938, 0.9000 and 0.9012 which is much lower than the FRF, which indicates that the pesticide usage prediction using FRF yield better results.

5.2 Recall Rate comparison

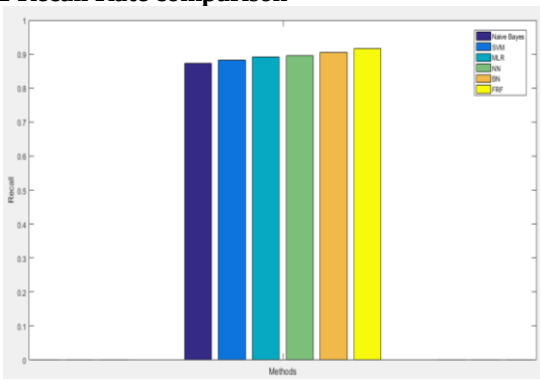

Fig.3. Recall comparison

From the aforementioned Figure 3 the graph describes the relation of the recall rate for the estimation of pesticide use. The methods such as FRF, Naïve Bayes, SVM, MLR, NN, and BN Classifier are performed. When the number of data is increased linearly according to the value of the recall. From this table, it is discovered that the proposed FRF has a higher recall rate of 0.9167 than previous approaches such as Naïve Bayes, SVM, MLR, NN and BN, with a recall rate of 0.8723, 0.8821, 0.8922, 0.8950 and 0.9054 which is far lower than the FRF, suggesting that the estimation of pesticide utilization using the proposed FRF produces improved performance. This is because the fuzzy approach will improve the nearest target detection results of pesticide usage.

5.3 ROC (f-measure) Rate comparison

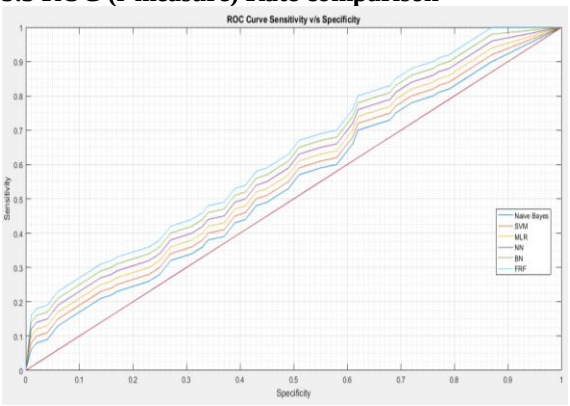

Fig.4. ROC comparison

5.4 Accuracy comparison

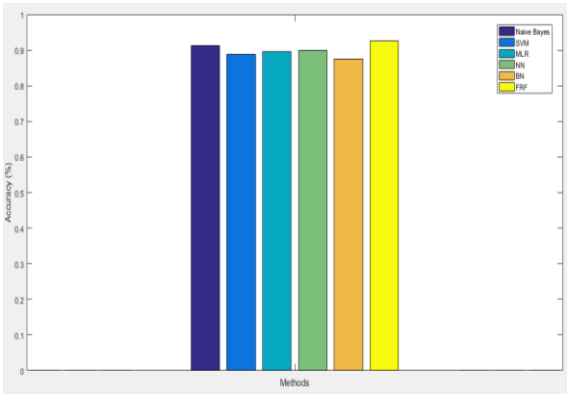

Fig 5. Accuracy comparison

The graph shows that the accuracy comparison for pesticide use prediction is explained from the above fig.5. The methods such as FRF, Naïve Bayes, SVM, MLR, NN, and BN Classifier are performed. When the number of data is increased linearly according to the accuracy value. From this table, it is found that the suggested FRF has a higher

accuracy rate of 0.9250 percent relative to previous approaches such as Naïve Bayes, SVM, MLR, NN and BN, with a recall rate of 0.9125 percent, 0.8875 percent, 0.8950 percent, 0.9000 percent and 0.8750 percent much lower than the FRF. Thus the output explains that the proposed FRF algorithm is greater than the existing algorithms in terms of better prediction of pesticides matching results with high precision rates. The explanation behind this is because current strategies often have a poor performance rate and has a strong probability of triggering misdetection of pesticide use.

VI. CONCLUSION

Through this research article, in the framework of fuzzy random forests, was introduced a novel approach to the creation of a fuzzy decision tree. While random forests have proved to be very reliable classifiers, they have not been studied extensively in the fuzzy community: only a few works have suggested solutions to the generation of fuzzy random forests and predicted the usage of pesticides in benchmarking datasets. However, these approaches create fuzzy partitions of the continuous attributes prior to beginning the learning algorithm execution. Unlike these approaches, the fuzzy partitions created by adopting an approach that iteratively zoom in on specific intervals of the universe during tree generation. Results from the experiment show that the proposed FRF method is much better with accuracy rate of 0.9250% than other methods such as Naïve Bayes, SVM, MLR, NN and BN. Predicting the effects of pesticide usage on human safety in agriculture may be addressed in future.

REFERENCES

[1]. Burns, T., US Patent No. 358498, 1995.Mahmood, I., Imadi, S. R., Shazadi, K., Gul, A., & Hakeem, K. R. (2016). Effects of pesticides on environment. In Plant, soil and microbes (pp. 253-269). *Springer*, Cham.

[2]. Chakraborty, S., & Newton, A. C. (2011). Climate change, plant diseases and food security: an overview. *Plant Pathology*, 60(1), 2-14.

[3]. Sánchez-Bayo, F. (2011). Impacts of agricultural pesticides on terrestrial ecosystems. *Ecological impacts of toxic chemicals*. Bentham Science Publishers Ltd, USA, 63-87.

[4]. Lechenet, M., Dessaint, F., Py, G., Makowski, D., & Munier-Jolain, N. (2017). Reducing pesticide use while preserving crop productivity and profitability on arable farms. Nature Plants, 3(3), 1-6.

[5]. Ge, Z., Song, Z., Ding, S. X., & Huang, B. (2017). Data mining and analytics in the process industry: The role of machine learning. *Ieee Access*, 5, 20590-20616.

[6]. Khan, F., & Singh, D. (2014). Association rule mining in the field of agriculture: a survey. *International Journal of Scientific and Research Publications*, 329.

[7]. Berrar, D. (2018). Bayes' theorem and naive Bayes classifier. *Encyclopedia of Bioinformatics and Computational Biology*: ABC of Bioinformatics, 403.

[8]. Ding, S. F., Qi, B. J., & Tan, H. Y. (2011). An overview on theory and algorithm of support vector machines. *Journal of University of Electronic Science and Technology of China*, 40(1), 2-10.

[9]. Uyanık, G. K., & Güler, N. (2013). A study on multiple linear regression analysis. *Procedia-Social and Behavioral Sciences*, 106(1), 234-240.

[10]. Yadav, N., Yadav, A., & Kumar, M. (2015). An introduction to neural network methods for differential equations (pp. 13-15). *Netherlands: Springer*.

[11]. Nguyen, L. (2013). Overview of Bayesian Network. *Science Journal of Mathematics and Statistics*, 2013.

[12]. Donatelli, M., Magarey, R. D., Bregaglio, S., Willocquet, L., Whish, J. P., & Savary, S. (2017). Modelling the impacts of pests and diseases on agricultural systems. Agricultural systems, 155, 213-224.

[13]. P. K. Kosamkar, V. Y. Kulkarni, K. Mantri, S. Rudrawar, S. Salmpuria and N. Gadekar, "Leaf Disease Detection and Recommendation of Pesticides Using Convolution Neural Network," 2018 *Fourth International Conference on Computing Communication Control and Automation (ICCUBEA*), Pune, India, 2018, pp. 1-4.

[14]. Dahikar, S. S., & Rode, S. V. (2014). Agricultural crop yield prediction using artificial neural network approach. *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering*, 2(1), 683-686.

[15]. Burdur, Z., & ATAY, C. E. (2018). An Analysis of Pesticide Use for Cotton Production through Data Mining: The Case of Nazilli. *Anadolu Üniversitesi Bilim Ve Teknoloji Dergisi A-Uygulamalı Bilimler ve Mühendislik*, 19(3), 732-747.

[16]. Linhart, C., Niedrist, G. H., Nagler, M., Nagrani, R., Temml, V., Bardelli, T., ... & Hertoge, K. (2019). Pesticide contamination and associated risk factors at public playgrounds near intensively managed apple

and wine orchards. *Environmental Sciences Europe*, 31(1), 28.

[17]. Mahmood, I., Imadi, S. R., Shazadi, K., Gul, A., & Hakeem, K. R. (2016). Effects of pesticides on environment. *In Plant, soil and microbes* (pp. 253-269). *Springer*, Cham.

[18]. Zikankuba, V. L., Mwanyika, G., Ntwenya, J. E., & James, A. (2019). Pesticide regulations and their malpractice implications on food and environment safety. *Cogent Food & Agriculture*, 5(1), 1601544.

[19]. Morteza, Z., Mousavi, S. B., Baghestani, M. A., & Aitio, A. (2017). An assessment of agricultural pesticide use in Iran, 2012-2014. *Journal of Environmental Health Science and Engineering*, 15(1), 10.

R.Beulah, et. al. "Prediction of Pesticides Used For Crop Production on the Environment Using Fuzzy Random Forest Classifier." *International Journal of Engineering Research and Applications (IJERA)*, vol.10 (09), 2020, pp 38-45.