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Application of Data Analysis and Soft Computation to Model the Need of Crop Insurance for the Indian Farmers

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Abstract

A very high level of uncertainty is associated with agriculture in the form of natural, social and human-related actions. Farmers incur heavy losses whenever their farmlands are affected. Crop insurance is the answer to such losses that existed as an institutional response to the nature-induced risk. Although crop insurance is advantageous, there are some drawbacks in implementation because of which the farmers are not willing to opt for it. Hence, there is a demand to model the need of crop insurance for Indian Farmers. For this purpose, the paper is divided into two parts. The first part involves applying exploratory data analysis (EDA) to correlate the factors with the farmers' responses. A correlational analysis is also conducted to study the relationship between different factors. The second part involves the application of three machine learning (ML) algorithms, namely, Logistic Regression (LR), Random Forest (RF) and Gradient Boost classifier (GB) to meet the aims and objectives of the paper. The performance of the three ML models is scrutinised based on their accuracy and predictive capability. The ML model with the best performance is chosen to determine the threshold value below which there is a high likelihood of a farmer opting for crop insurance. The strength of the proposed approach is its practical applicability.

Keywords: *Crop insurance, Exploratory data analysis, Correlational analysis, Machine learning model, Threshold value computation.*

Application of Data Analysis and Soft Computation to Model the Need of Crop Insurance for the Indian Farmers

1. Introduction

Agriculture is the source of livelihood for 58% of the Indian population [1]. It contributes 14.4% in gross value added [2]. A very high level of uncertainty is associated with it in the form of natural, social and human-related actions [3]. The highest risk clubbed with farming is the uncertainty of crop yields. The inherent uncertainties in weather, yields, prices, Government policies, global markets, and other factors that impact farming can cause wide swings in farm income. India is also identified as a highly vulnerable country to climate change [4]. In recent literature, it has been concluded that in India, there is a significant rise in temperature, frequent heat waves, droughts, extreme precipitation events, and intense cyclonic activities [5 – 7]. Farmers are always at the mercy of nature as the crop yield is highly affected by natural factors such as rain, humidity, temperature, amount of nitrogen, phosphorus and potassium in the soil, etc. [8]. Farmers with limited resources are more prone to such risks, especially if they result in disastrous losses. There is a need to protect farmers from agriculture variability. Crop insurance is the answer to such losses that existed as an institutional response to nature-induced risk [9].

According to [10], crop yields need optimum temperature and rainfall. A slight temperature rise reduces crop yields and encourages the growth of weeds and pest proliferation. Changes in precipitation increase the probability of crop failure and, in the long term, can result in production declines. In India, in 2021, over 5 million hectares of agricultural land will be affected due to heavy precipitation, resulting in a loss of approximately ₹23,186.4 crores [11]. However, in some other states of India, crop yields are affected by drought. It is estimated that about 3.1 % of the Gross Domestic Product (GDP) is decreased due to droughts, accounting for approximately ₹ 39,000 crores [12]. The crop loss due to drought and flood is directly proportional to the land size, thereby incurring heavy losses to the medium or large-scale farmers. It is estimated that from 2008 to 2012, the farmers of the state of Odisha in India incurred a loss of ₹11,253/- per acre due to floods and ₹3,588/- per acre due to drought [13]. Another primary reason for crop loss is weeds. Annually, in India, it is estimated that approximately $11 billion or ₹85,745 crores of economic losses occur only due to weeds [14].

These losses incurred from the crop yields are the primary reason for farmer suicides in India., followed by drought, flood, debt, poor farmer-related economic policies etc. [15]. Farmers' suicides have to be viewed as a "National Disaster", the statement of the Ex-Prime Minister of India, Dr Manmohan Singh, himself a distinguished economist, opens our eyes to the agrarian crisis that haunts the country today. It is reported in [16] that climatic change has created a stress situation among farmers that compounds the farmers' debt burden, which leads to some farmers committing suicide. According to [17], the percentage of farmers in debt in Andhra Pradesh, Punjab, Karnataka, and Maharashtra was 70%, 65%, 61%, and 60%, respectively. In 2012, it was reported that about 135,445 people committed suicide in India, of which approximately 11.2% were farmers [18]. Moreover, 76% of the farmers committing suicides are from Maharashtra, Andhra Pradesh, Karnataka, Madhya Pradesh and Kerala [19].

Although with the increase in the number of farmers' suicide, the decline in the share of the nation's Gross Domestic Product (GDP) and the number of cultivators, the climate-sensitive agricultural sector continues to be the primary source of livelihood in India [20]. Crop insurance schemes were introduced to curb the farmers' distress from crop loss. In general, the principles of crop insurance agreed to pay the insured farmers the valuation of the unexpected loss of projected crop yields or profits from produce sales at the market over a period of time. Crop insurance protects the farmer against financial losses due to uncertainties that may arise from crop failures/losses arising from named or all unforeseen perils beyond their control. However, to avail of the insurance schemes' benefits, the insured farmers pay a premium either monthly or quarterly or half-yearly or annually [3].

The chronology of the Indian crop insurance schemes since 1985 is shown in table (1).

Table 1: Chronology of Indian crop insurance schemes

Sl. No.	Name of crop insurance scheme	Starting year	Ending year
1	Comprehensive Crop Insurance Scheme (CCIS)	1985	Summer 1999
2	National Agricultural Insurance Scheme (NAIS)	1999 – 2000	Winter, 2015 – 16
3	Pilot Farmers Income Insurance Scheme (FIIS)	Summer 2003	Winter 2003 – 04
4	Pilot Weather Based Crop Insurance Scheme (WBCIS)	Summer, 2007	Summer, 2013
5	Pilot Coconut Palm Insurance Scheme (CPIS)	2009 – 10	Summer, 2013

6	Pilot Modified NAIS (MNAIS)	Winter, 2010 – 11	Summer, 2013
7	National Crop Insurance Programme (NCIP) with component schemes of MNAIS, WBCIS and CPIS	Winter, 2013 – 14	Winter 2015 – 16
8	Pradhan Mantri Fasal Bima Yojana (PMFBY)	April, 2016	Present

The cumulative statistics of the crop insurance schemes for the NAIS, MNAIS, WBCIS and CPIS are shown in table 2.

Table 2: Cumulative statistics for the schemes NAIS, MNAIS, WBCIS and CPIS.

Total farmers insured (in Crores)	Total areas insured (in Crores Hectares)	Total premium collected (in Crores ₹)	Total claim paid (in Crores ₹)	Total farmers benefitted (in Crores)
36.9	51.3	31300.8	58711.4	13.5

In general, crop insurance schemes are categorised into three types. The first type is Single/Multiple Peril Crop Insurance, where the insurers are provided with financial coverage to manage risks arising from weather-related losses, such as a flood, drought, etc. [21]. The second type is Actual Production History which includes losses due to wind, hail, insects, etc. It also provides coverage for lower yields and compensates for the difference between the estimated and the real crop yields [22]. Finally, the third type is Crop Revenue Coverage which is based not only on the crop yield but on the total revenue generated from this yield. In case of a drop in crop price, the difference is covered by this type of crop insurance [23]. However, the crop insurance schemes in India are poorly designed and structurally flawed [24]. Low penetration of crop insurance, delay in the distribution of compensation, the inadequacy of the compensation compared to the costs, and compulsory clubbing of insurance with loans forcing farmers to pay premiums are the most common reasons for this failure [25].

1.1. Motivation and Novelties

From the literature reviewed for the study, some of the gaps that are identified are as follows:

a. Very little literature has correlated the factors with the response in the research domain of Crop Insurance.

b. Although a lot of literature has modelled the need for Crop Insurance, few papers have applied ML model for this purpose.

c. The number of research papers finding the threshold values of the factors below which a farmer will opt for Crop Insurance is minimal.

To achieve the aims and objectives of the research paper, the research is divided into two parts; the first part involves the application of exploratory data analysis (EDA). The EDA correlates the factors affecting Crop Insurance with the farmer's response to whether they are willing to opt for Crop Insurance. The dataset was modelled using three machine learning models to answer the following two points. The models were then scrutinised based on accuracy and predictive capability to determine the best model out of the three. The model with the best performance is selected to computer decision trash old value for the independent variables.

Section 2 of the paper describes the data sets and the preliminary methodologies adopted for analysing the dataset. Section 3 of the paper describes the problem statement, followed by the results obtained after employing the methodology in the problem in Section 4. Section 5 is the conclusion of the paper.

2. Materials and Methods

This section of the paper briefly discusses the dataset collected for the study. It also briefly describes the research questions and the methodology adopted for the study.

2.1. Data acquisition

The data considered for the study were gathered from the subsequent related literature in the domain. Based on the objective of the paper, the required data were extracted. All the data collected and used for the study are appropriately cited.

2.2. Preliminary concepts

In this section of the paper, the preliminary concept adopted for analysing and modelling the dataset is briefly discussed. This paper has made use of empirical analysis, analytical study, pattern analysis, and trend analysis. Empirical analysis is the study where a concrete conclusion is drawn from "verifiable" evidence. There are two ways of gathering empirical evidence: qualitative and quantitative [26]. Mainly quantitative research methods have been used in this study. Under quantitative research methods, secondary survey research has been adapted for analysing the dataset. One of the most significant advantages of using quantitative analysis is that it can focus on facts or a series of information [27]. Another benefit of employing secondary research under quantitative methods is the availability of similar research in the domain and deriving more useful and consequential information from the analysis [28].

2.2.1. Exploratory Data Analysis (EDA)

This paper performs an EDA to draw the relation between the factors and outcome. EDA is used to analyse and investigate data sets and summarise their main characteristics, often employing data visualisation methods. It helps determine how best to manipulate data to answer the desired questions, aiding in discovering patterns, spotting anomalies, testing a hypothesis, or checking assumptions. Its primary purpose is to visualise the data before arriving at any conclusions or assumptions [29].

a. Pie-chart analysis

Pie-chart is a kind of statistical analysis used for comparing the proportion of data in different categories. A pie chart is a circle divided into different segments representing each category's observation. The importance of a specific factor with respect to others is determined by the proportionate size of the segment representing the factors corresponding to the other factors [41].

b. Correlational analysis

Correlational analysis is a statistical technique employed in measuring the degree of relationships between variables. The advantage of using correlational analysis is that the researchers can determine the direction and strength of the variables' relationship [42]. The degree of relationship between the variables is measured by computing the correlation coefficient value, which ranges from -1 to +1.

2.2.2. Machine Learning (ML)

Machine learning (ML) is a field of study that amalgamates the concepts of computer science, mathematics and statistics for the software applications to become more accurate in predicting or simulating the output scenarios without being explicitly programmed to do so. In the present technologically advanced world, ML is the fastest growing field, with its application varying from robotics [30], economics [31], agriculture [32], crypto price prediction [33] etc., to name a few. In the present study, three ML algorithms, viz. logistic regression (LR), Random Forest (RF) and Gradient boost classifier (GB), were employed for developing the prediction models.

a. Logistic Regression (LR)

LR is a supervised ML algorithm often applied in problems with binary outputs. LR predicts the probability of an event occurring based on the given independent dataset. Since the outcome of the dataset for the LR model is the probability of occurring, it is always bounded between 0 and 1. In the field of ML, LR is advantageous to use because it is easier to implement, interpret, and very efficient to train [34]. The governing formula for the LR model is shown in Eq. (1).

$$p = \frac{1}{1+e^{-\left[a+\sum_{i=1}^{n}(b_i.x_i)\right]}} \tag{1}$$

Where p is the probability of the outcome, x_i is the i^{th} independent variable, b_i is the coefficient of x_i and the a is the intercept.

b. Random Forest (RF)

RF is a supervised ensemble ML algorithm often applied for the decision making problems. RF integrates the decision from multiple decision trees (DT) to reach at a single result. The disadvantage of applying DT is that it is prone to overfitting and bias. Hence, multiple DTs ensemble to form RF that can predict the outcomes more accurately and precisely particularly in the scenarios when the individual DT are uncorrelated with each other.

c. Gradient Boosting Classifier (GB)

GB is another supervised ML algorithm mostly used for predicting decision outcomes. GB algorithms combine a set of weak ML algorithms in order to create a strong ML model. In this algorithm, the predictor variable tries to improve on its predecessor by reducing the error by fitting a new predictor to the residual errors made by the previous predictor at each iteration [35].

3. The case study

In this section of the paper, a brief description of the case study along with the different assumptions, dataset and data preprocessing is discussed.

3.1. The problem statement

The comprehensive intention of the present study is to model the need of crop insurance for Indian farmers. Crop insurance is the protection policy that covers agricultural producers against unexpected loss of projected crop yields or profits from produce sales at market. Some of the state-of-the art literature in the topic of crop insurance depicted it in bad light due to the fact that there is no protection from independent risks, bank involvement, damage compensation etc., to name a few [36]. As a result of the disadvantages of crop insurance, there is a need to model the decision outcome for having crop insurance for the farmers.

3.2. The dataset

In the present study, the dataset used for modeling the need of crop insurance involves the factors such as the insurance premium, previous reviews, gender and yield damage. The data are extracted from various literatures and secondary surveys done on the topic of the study. The factors are linked with the outcomes of taking the decision of having crop insurance or not. The factors are both quantitative as well qualitative in nature. Also the units of the factors are different and hence there is a need for data preprocessing.

3.3. Data preprocessing

Data preprocessing in ML transforms the raw data into a useful and efficient format. The steps for data preprocessing involves converting the dataset into unit less numbers so that all the different factors can be correlated to the outcomes [37]. In this step the dataset are thoroughly cleaned and scaled using the feature scaling method. The feature scaling is done using the Eq. (2).

$$y = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

Where y in Eq. (2) is the scaled value of the factor, x is the value of the independent variable, x_{min} and x_{max} is the minimum and maximum value of the independent variables.

4. Results and discussions

In this section of the paper, the results obtained from analysing the datasets and a brief discussion is presented. The analysis of the dataset is done in two parts. The first part involves analysing the factors and deriving the correlation matrix using the EDA. The second part involves developing the data driven model using ML algorithms viz. the LR, RF and GB. For conducting the analyses of the dataset and developing the ML models, the programs are coded in Python 3.8 and run on a 64-bit Windows 11 system with 8 GB RAM and i5, 1.6GHz processor. The different libraries imported for analysing the dataset and developing the ML models are tabulated in table 3.

Table 3: List of libraries imported

Sl. No.	**Library imported**		**Importance**	**Sl. No.**	**Library imported**	**Importance**
1	Numpy		For array operation	**2**	Pandas	For data handling
3	Matplotlib		For data visualisation	**4**	Seaborn	For visualising random distribution
5	Sklearn		For developing ML models			

4.1. Result from the EDA

In this section of the paper, the observations made from the EDA are discussed in brief.

4.1.1. Outcome distribution with gender

An EDA analysis is conducted for response distribution over gender. Figure (1) shows the pie chart breakdown for the response distribution of the gender group for the collected dataset.

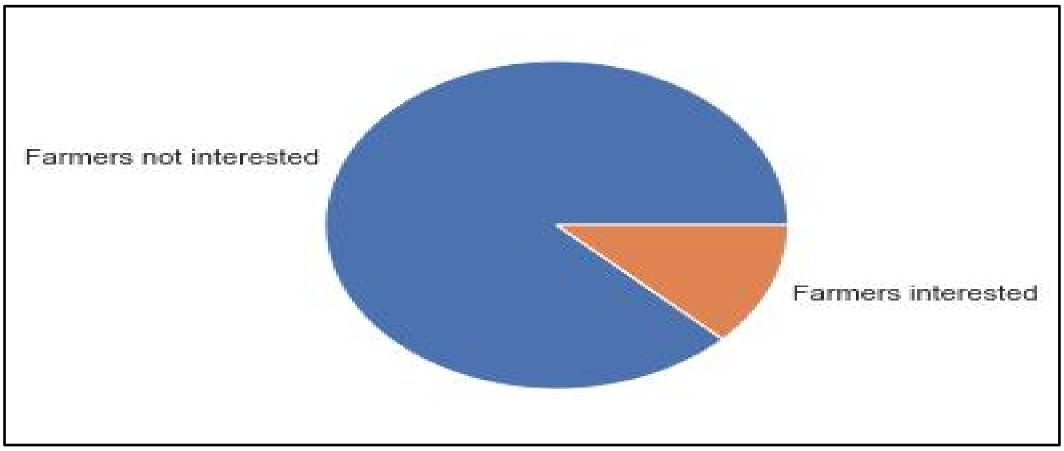

Figure (1): Pie-chart breakdown of the response distribution by the gender group

Figure (2) shows the pie chart breakdown for the gender group that has opted for the crop insurance for the collected dataset.

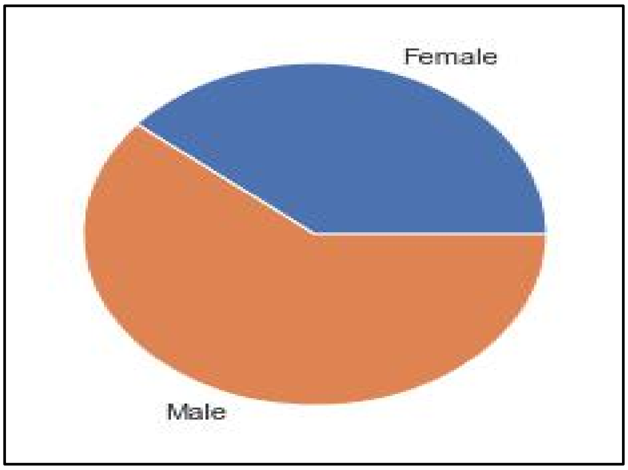

Figure (2): Pie-chart breakdown for the gender group opting for crop insurance

From the figure (1), it is observed that 12.25% of the farmers are opting to have crop insurance whereas the remaining 87.75% farmers are not. Out of all the farmers who are opting for the crop insurance, around 38.93% are female and 61.07% are male as evident from the figure (2).

4.1.2. Outcome distribution with age

In order to analyse the response distribution with age, a distribution curve and a boxplot is plotted in figure (3) and (4) respectively.

From figure (3), it is observed that the maximum number of participants lie in the age group of 20 – 30 years. It is also observed that the age of the participants lies within 20 to 88 years. From figure (4) it is evident that the median age of the farmers who are not opting for crop insurance is around 35 years of age. It is also to be noted that the median age of the farmers who are opting for crop insurance is around 42 years of age. The lower age group farmers are mostly not willing to take the crop insurance as they feel that there is no to very little benefit of crop insurance. In addition, the lower age group farmers also feel that the burden of paying the premium is more in comparison to the benefits from the crop insurance [38].

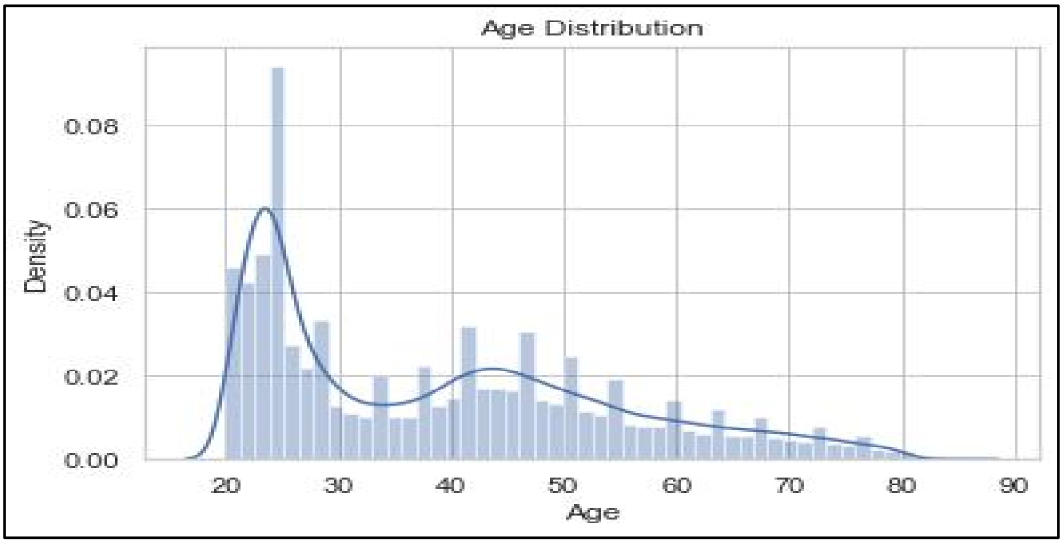

Figure (3): Distribution curve for age-density distribution

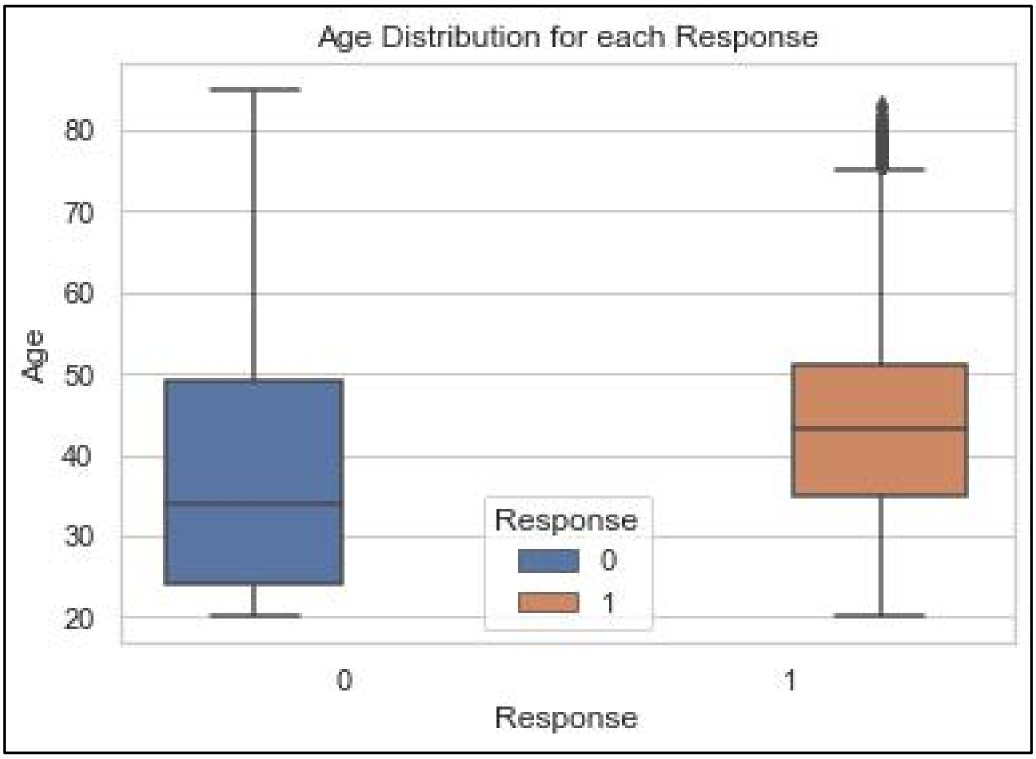

Figure (4): Boxplot for age distribution for each response

4.1.3. analysis based on response from previously insured farmers

In order to analyse the response distribution with previously insured farmers a pie chart breakdown for the previously insured group with respect to the response of the farmers and the farmers opting for the crop insurance is shown in figure (5) and (6) respectively.

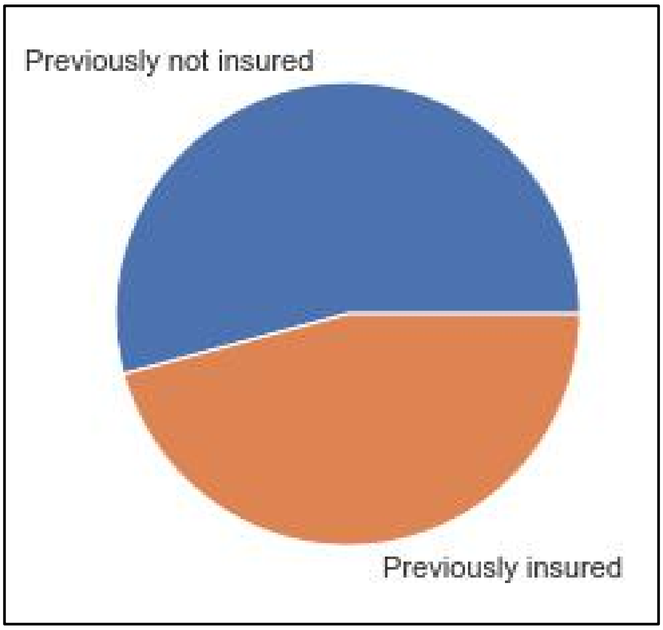

Figure (5): Pie-chart breakdown for the participants based on previously insured or not

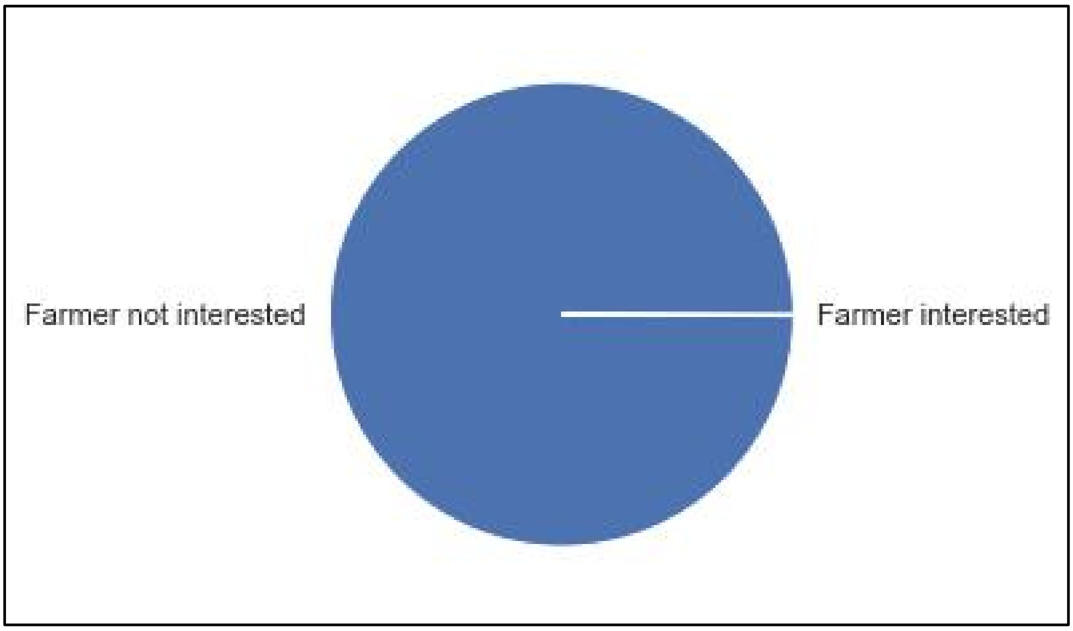

Figure (6): Pie-chart breakdown for the farmers who are previously insured based on their interest

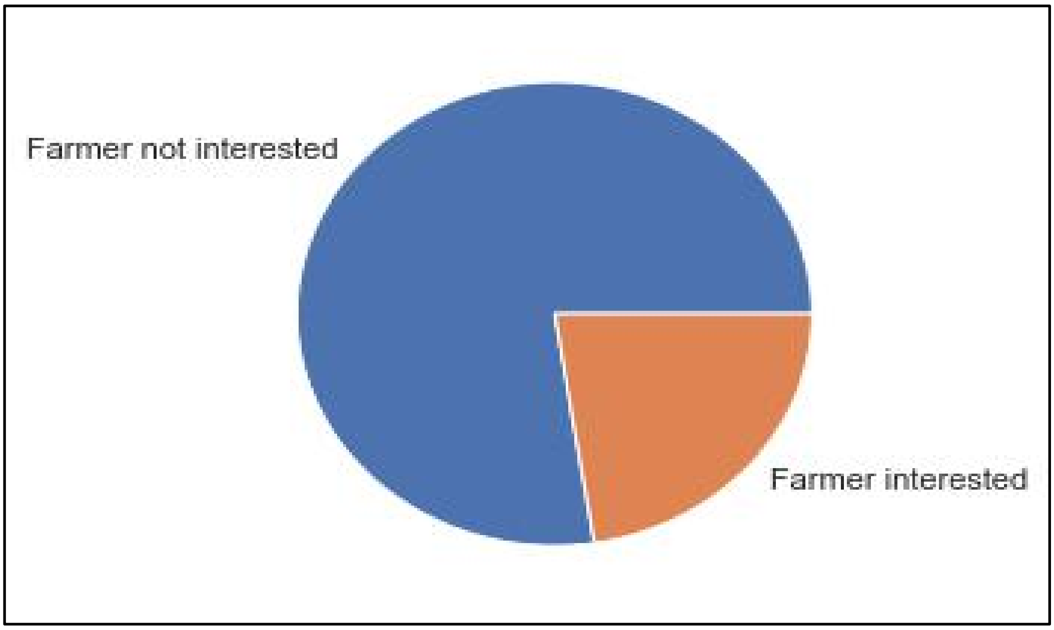

Figure (7): Pie-chart breakdown for the farmers who are not previously insured based on their interest

From the pie-chart analysis, it is observed that 45.82 % of the farmers are previously insured and out of them only 0.09% farmers are opting to renew their crop insurance in the upcoming years. It is also observed that around 54.18% of the farmers are not previously insured and out of them 22.55 % are willing to opt for crop insurance in the upcoming years.

From the analysis, it is observed that about 250 times more number of farmers who are not previously insured are willing to opt for one in the upcoming years. This is due to the fact, there is a sense of fear because of which crop insurance seems alluring for them [39]. On the other hand, about 0.09% of the farmers are willing to continue their crop insurance policy as they do not feel confident enough about the crop insurance [40].

4.1.4. analysis based on response from farmers whose yields are damaged

For analysing the response of the farmers based on yield damage, a pie chart analysis is conducted. Figure (8), (9) and (10) shows the breakdown of the dataset based on the yield damage and the response of the farmers whose yield is damaged.

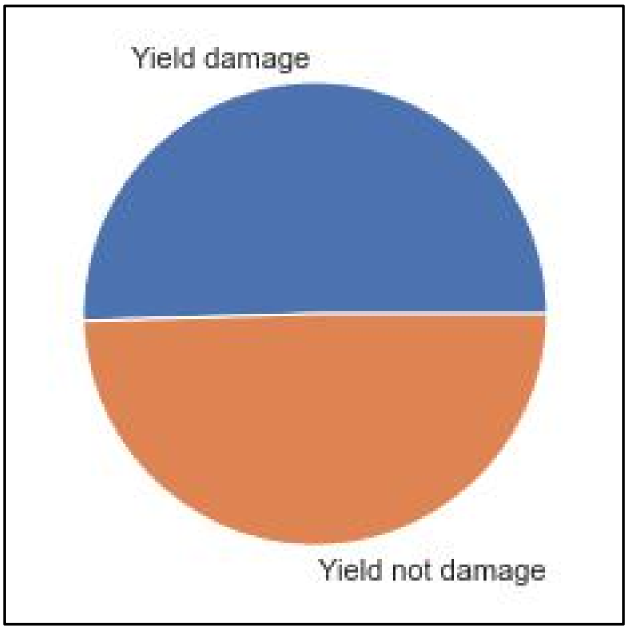

Figure (8): Pie-chart breakdown of the farmers whose yield are damaged

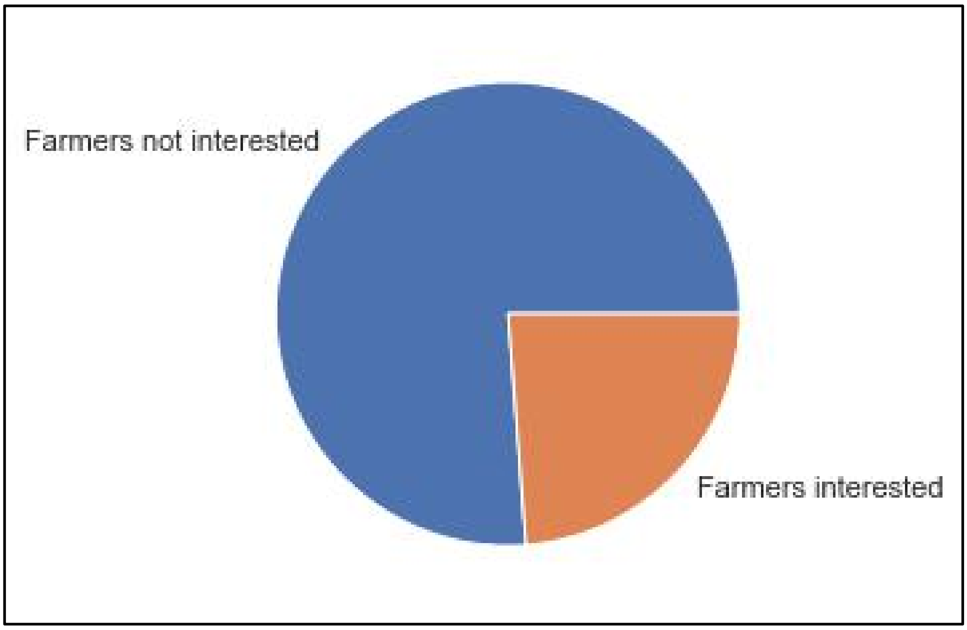

Figure (9): Pie-chart breakdown of the farmers who are interested based on yield damaged

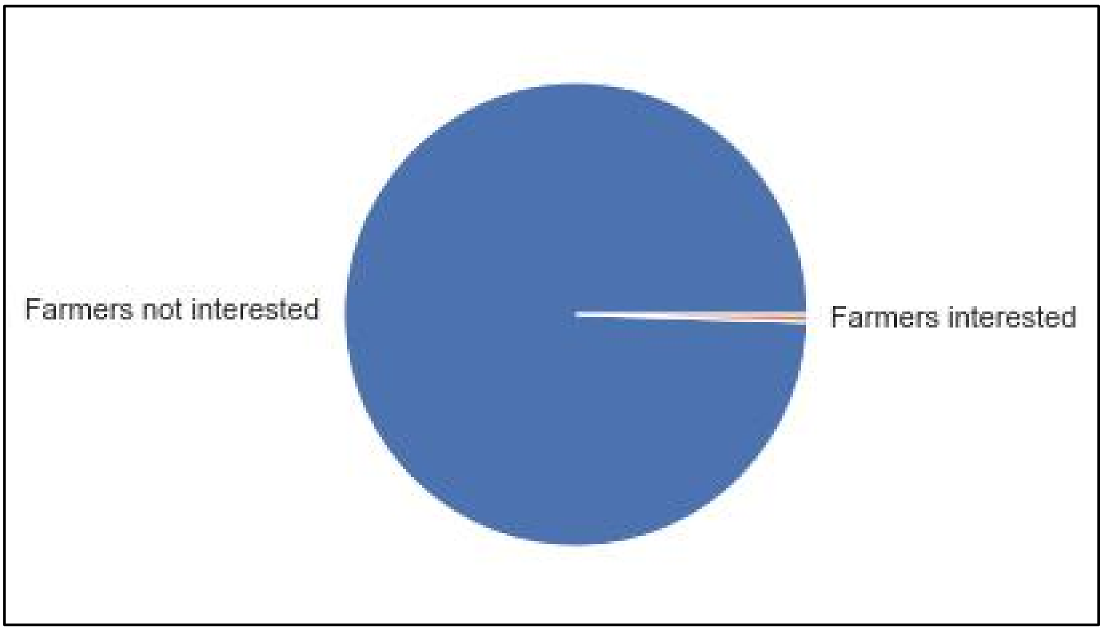

Figure (10): Pie-chart breakdown of the farmers who are interested based on yield not damaged

From the pie-chart analysis based on the yield damage and response of the farmers, it is observed that the yield of 50.48 % farmers is damaged. Out of them, 76.23 % of the farmers whose yields are damaged are not interested in buying crop insurance in the upcoming years. However, 99.48 % of the farmers whose yields are not damaged are not willing to buy crop insurance in the upcoming years.

4.1.5: Correlational analysis

Figure (11) shows the correlational analysis between the different factors considered in the study.

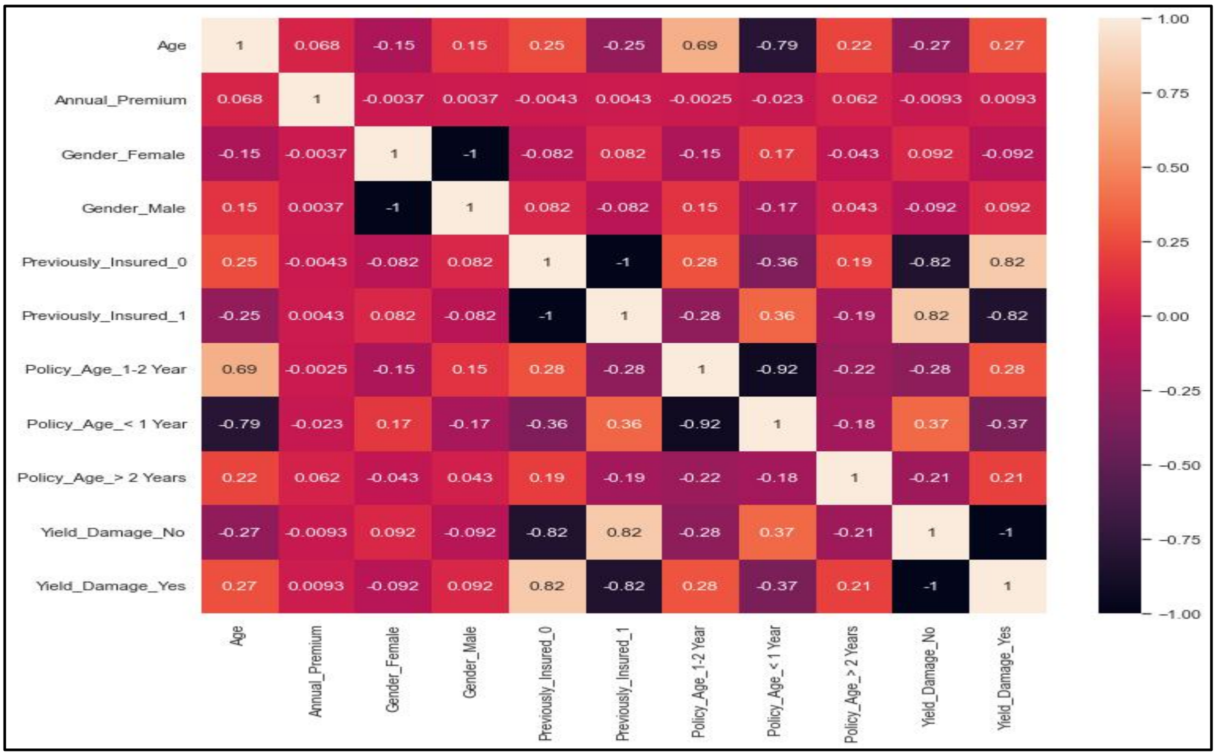

Figure (11): Heatmap showing the correlational matrix.

Some of the points observed from the correlational analysis are as follows:

1. More young females are associating with farming in comparison to male farmers.
2. Female farmers are paying lower annual premiums than the male farmers.
3. Farmers whose yield is damaged are willing to pay more annual premium than the farmers whose yield is not damaged.
4. There are more female farmers who are not previously insured in comparison to the male farmers.

4.2. Machine learning modeling

For creating the ML models the list of libraries imported is shown in table 4. The collected dataset is split in a 70:30 ratio where 70% of the data were used for training the models and the remaining 30% data were used for testing the model. Feature scaling method is employed for standardising the dataset as shown in section 3.3 of the paper. Then the predictive model is developed using LR, RF and GB. The values of the AUC (Area Under the Curve) score of the Receiver Operating Characteristics (ROC) curve, accuracy, false negative and true positive are tabulated in table 4. The ROC curve for the three ML models is shown in figure (12).

Table 4: Summary table of the ML models.

Sl. no.	Algorithm	AUC score	Accuracy	False negative	True positive
1	LR	0.8283	0.8691	66166	80
2	RF	0.7759	0.8007	60115	920
3	GB	0.8461	0.875	66697	0

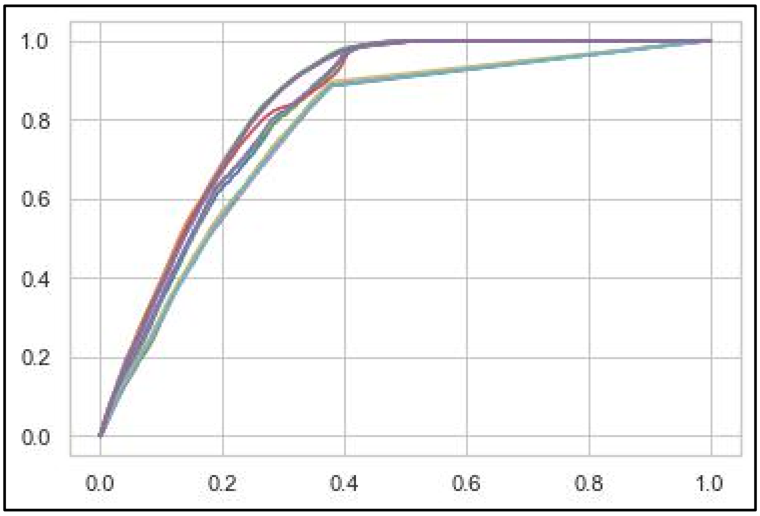

Figure (12): ROC for the ML models.

AUC represents the probability under the ROC curve. Out of the three ML models, GB classifier has the maximum AUC score, accuracy and highest correct predictive capability. Therefore the GB classifier model is used to determine the threshold value for the classification if a farmer is opting to decide to take crop insurance or not.

4.3. Computing the threshold value

A threshold value is the set of independent values below which there is a likelihood of occurring of the event and above which there is a likelihood of not occurring of the event. In order to compute the threshold value, the precision and the recall curve is plotted in figure (13).

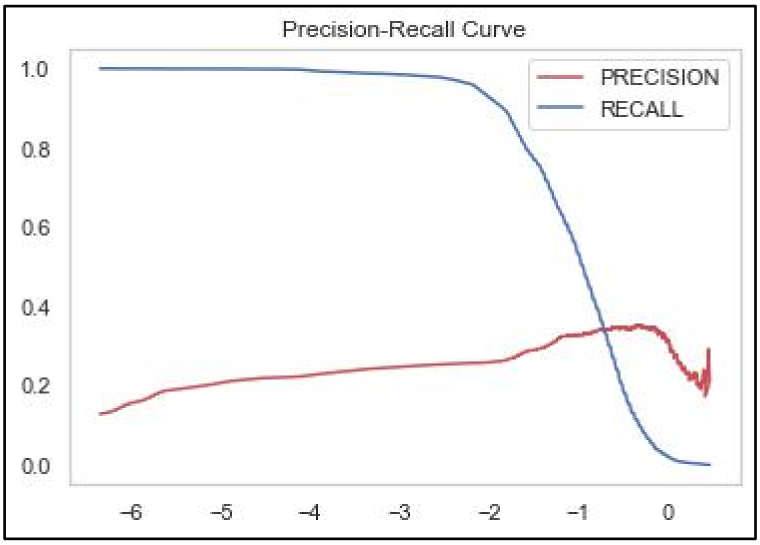

Figure (13): Precision and recall curve

The ordinary value of the point of intersection of the precision and recall is the decision threshold value of the GB classifier. The threshold value obtained for the particular problem is 0.36656692. The set of independent values computed for decision threshold is shown in table 5.

Table 5: Values of independent variables computed for decision threshold

Gender	**Age**	**Annual premium**	**Previously insured**	**Policy age**	**Yield damage**
Male	39	30564.40	No	1 - 2 years	Yes

5. Conclusion

The present research models the need of Crop Insurance for Indian farmers based on factors such as gender, age, annual premium paid, yield damage and past experience. Although various studies have been undertaken in this particular research domain, there is very little to no research that can model the need for Crop Insurance using ML models. In the literature, Crop Insurance is portrayed as a necessary evil. Various advantages and disadvantages of crop insurance have been put down in the existing state-of-the-art literature.

In this research paper, to achieve the aims and objectives, the research involves the application of EDA to drive the relationship between the factors and the response. From the analysis, it is observed that most young farmers are willing to opt for Crop Insurance as there is a sense of fear among them. However, the old-age farmers aren't ready to buy the Crop Insurance as they feel it has very little to no benefit for them and the annual premium paid is a burden. The analysis also concludes that the female farmers pay less annual premium than the male farmers. Because of this reason more female farmers are willing to buy the Crop Insurance than their male counterparts.

The research paper also involves the application of three ML models namely LR, RF and GB to model the need of crop insurance for Indian farmers. The AUC score, accuracy, false negative and true positive for the three models is shown in table 4. On scrutinising the performance of the ML models, it is found that the result obtained from the GB classifier is better in comparison to the other two models. Hence it is used for computing the decision threshold values. The decision threshold value is the ordinate value for the point where the precision curve intersects with the recall curve. The computed decision threshold value is 0.36656692. The computed value for the set of independent variables at the decision threshold is shown in table 5. A farmer is likely to buy a Crop Insurance if the value of the independent variables is below the value shown in table 5. Above the threshold value, there is a higher probability that a farmer will not buy Crop Insurance. From the overall discussion and the result obtained, it can be concluded that the Gradient Boost Classifier is able to model the need of Crop Insurance for Indian farmers based on their gender, age, annual premium paid, yield damage and as well as from their past experience on having a Crop Insurance.

In India, crop insurance is mostly put in a bad light due to its poor designing. Hence the farmers hesitate to get crop insurance. Due to this, the insurance companies suffer and hence from their perspective a predictive model is needed that could forecast the decision threshold that will help the companies to understand the needs of farmers and design the policy accordingly. Moreover, including factors such as amount of the yield damage, area of farmland damaged by natural calamities for each farmer, analysing the process of claim settlement and involving those factors for modeling the need of crop insurance could enhance the output of the present study is the future scope of the present study.

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