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Retraction

Retracted: Implementing Machine Learning for Smart Farming to Forecast Farmers' Interest in Hiring Equipment

Journal of Food Quality

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] M. Rakhra, S. Sanober, N. N. Quadri, N. Verma, S. Ray, and E. Asenso, "Implementing Machine Learning for Smart Farming to Forecast Farmers' Interest in Hiring Equipment," *Journal of Food Quality*, vol. 2022, Article ID 4721547, 17 pages, 2022.

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Research Article

Implementing Machine Learning for Smart Farming to Forecast Farmers' Interest in Hiring Equipment

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Farmers' physical labor and debt are reduced as a result of agricultural automation, which emphasizes efficient and effective use of various machines in farming operations with the purpose of reducing physical labor and debt. It is a revolutionary idea in agriculture to create custom hiring centers, which are intended to make it easier for like-minded farmers to embrace technology/machinery for enhanced resource management practices. The study in question examines the significance of tool renting and sharing in the workplace. Rental and sharing equipment are two approaches that might be used to enable farmers to borrow equipment at a cheaper cost than they would otherwise have to pay for it. The following is a manual pilot study of 562 farmers in India to address the numerous challenges farmers face when looking for tools and equipment, as well as to determine their strong interest in the process of renting and sharing equipment. The study was conducted to address the numerous challenges farmers face when looking for tools and equipment and to determine their strong interest in the process of renting and sharing equipment. Farmers are divided into three groups according to the results of this poll: small, moderate, and large. Training and testing splits were used on the same data set in order to get a better understanding of the target variables. The data set for the survey was standardized in order to remove ambiguity. In this research, three different machine learning models were utilized: nearest neighbors, logistic regression, and decision trees. K-nearest neighbors was the most often used model, followed by logistic regression and decision trees. In order to get the best possible result, a comparison of the aforementioned algorithm models was carried out, which revealed that the decision tree is the better model among the others in this regard. Because the decision tree model is completely reliant on a large number of input factors, such as the kind of crop, the time/month of harvest, and the type of equipment necessary for the crops, it has the potential to have a social and economic impact on farmers and their livelihoods.

1. Introduction

The exponential population growth has strained agriculture. The agricultural land size is decreasing, but the demand to feed more and more mouths is increasing day by day. Natural and man-made factors have further hit food productivity. Therefore, mechanization is a panacea to most of the ills that afflict agriculture. Herein, the role of machines to carry out agriculture operations to maximize efficiency and yield comes into play. Without the optimal use of machines, agriculture production cannot be hiked. The developing countries lag behind in farm productivity owing to improper use of machines in various agriculture operations. On the other hand, automation of farming operations contributes significantly to rural and agricultural growth in many developing countries. Therefore, farmers must be encouraged to use machines in the field to increase efficiency and the produce of their products. It is also necessary to put

agriculture on automation the current rate of agricultural production required to feed the world population cannot be realized without mechanization [1]. Unfortunately, the use of farm machinery, unfortunately, is still under consideration in most parts of the world, including in some parts of India. It is high time that both the government and the private sectors should put their head together to push the country towards mechanized farming. Researchers are developing strategies to introduce the innovative system of mechanized farming to boost productivity and economy [2]. Mechanized farming has boosted their productivity besides strengthening the economy of their respective states.

1.1. Custom Hiring. Custom hiring center is a novel concept in farming that intends to stimulate the adoption of improved resource management strategies. These resource-sharing techniques at a cheaper cost to individual farmers are prevalent in some specific parts of the country. Under this innovative programme/strategy, agricultural equipment and tools are shared with the farming community [3–5]. Custom hiring centers enable needy farmers to gain the advantages of automation via the utilization of costly equipment. Some cooperative organizations have taken the initiative to offer agricultural equipment services to the farming community.

The role of the tractor in farming is undoubtedly immense. But studies revealed that a tractor was used for an average of 2 hours each day to carry out farming operations. In a developed village in Punjab, rented out tractor hours amount to 76 hours per year, and ploughing account for 61% of those hours. Thus, it is concluded that a farmer might run his farm with the help of custom-hired tools [6–8]. Farmers with less than 2.8 hectares of land are prospective consumers of agricultural tools via hiring/rental services. The state's mechanization level has also expanded dramatically [9, 10]. CHCs have thus played a major role in popularizing mechanized farming among farmers. CHCs make farm tools, machinery, and equipment available to farmers on a rental basis [11, 12]. While crop-specific tools and equipment (power units, tractors, tillers, and harvesters) are universally employed, resource sharing, mainly farm machinery and implements at a reduced cost to individual farmers, is a trend in some regions of the country [13–15]. Figure 1 displays a cycle of agricultural mechanisms that are under development.

Mechanization introduces accuracy and timeliness into agricultural activities, higher field covering over a shorter period of time, resource consumption, conservation of moisture content under stressful conditions, and supply of proper drainage [16, 17]. In 100 NICRA communities custom hiring centers (CHCs), farm tools are built, enabling farmers to overcome labor shortages and increase agricultural productivity. The custom hiring center is managed by a panel of farmers appointed by the Panchayati Raj. The Village Climate and Risk Management Committee determines the fees for renting the machines/implements (VCRMC). Additionally, this committee utilizes the cash earned by hiring costs to repair and maintain tools, with the remaining amount going
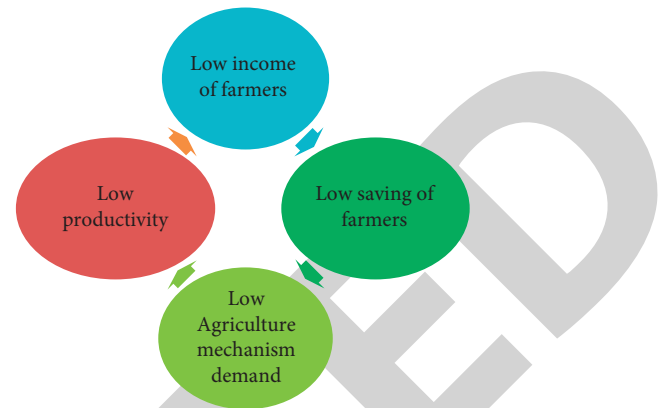

Figure 1: Various cycles of agriculture mechanisms under development.

into various financing schemes meant for the farmers [18, 19]. Custom hiring empowers small and marginal farmers to make use of expensive agricultural equipment. It enables farmers to operate expensive techniques and technology and complete the harvesting task in a short span of time. Also, it cuts labor and boosts crop intensity.

Custom hiring is not a cumbersome programme/strategy. It does not burden farmers. Under the programme, the user only needs to pay the contract/rental charges and security. Each model has been designed to determine the best hardware and asset assignment to reduce farming costs and convenience. The model is designed to choose appropriate agricultural tools and power sources with the purpose of accomplishing the task on time. This eliminates the shortage of produce, which is otherwise a consequence of delayed agricultural operations. The operationalization of the asset assignment programme in the year 2007 to minimize the cost turned out to be a success. Consequently, more interpretation was performed on supply chain measures and financial productivity in Punjab.

The small farmers saw their financial productivity go up by 17.02%, but large farmers displayed much higher economic productivity. The larger farmers have access to superior equipment. The smaller farmers cannot afford it. Yet mechanized farming pays to the smaller farmers. About 90% of the farmers in Punjab who own tractors use them less than 400 hours annually. Mechanization in this scenario plays a big role as it boosts growth. Custom hiring centers should pitch in here (they are already doing it) to make farming tools and equipment available to the small farmers at the appropriate time to get the intended results. This would mitigate the loan burden for the farmers as they usually borrow loans at a high rate of interest from commission agents [20].

All disciplines benefit from artificial intelligence-based technologies, which also assist to handle the issues encountered by numerous businesses, including the agricultural sector, in areas such as crop yield, irrigation, soil content sensing, crop monitoring, weeding, crop establishment, and other domains In order to supply high-valued applications of artificial intelligence in the indicated area,

agricultural robots are being developed. The agriculture industry is experiencing a crisis as the world's population continues to grow. Artificial intelligence has the potential to provide a much-needed solution to this pressing problem, however. Technological solutions powered by artificial intelligence have allowed farmers to generate more output with less input and even increase the quality of their product while also guaranteeing that their crops reach the market more quickly. In the year 2020, 75 million linked devices were used by farmers worldwide. Farms are predicted to create an average of 4.1 million data points per day by 2050, according to industry predictions.

Farmers often spend between 25% and 30% of their revenues on the purchase of equipment. Since this equipment is purchased from the local entrepreneurs at expensive prices, they increase the farming input cost. Labor is also hard to come by in Punjab as the rural population often migrate to cities in search of better employment avenues. In such a grim scenario, the role of mechanized farming assisted by CHCs increases manifold. This can accelerate agriculture growth, boost the economy, and also allow the Indian market to grow. This also has the potential to end the protracted issue of rural indebtedness and low profitability besides retaining small farmers in the agriculture business.

Over 20 crores Indian farmers lack access to agricultural equipment, and many of them have not even used them. Yet small farmers who own 86% of India's farmland are doing their best to transform agriculture production and revenue dramatically.

According to a report by NCRB, around 97% of suicides in the Malwa region were triggered by "agricultural debt." The bulk of unfortunate among them are small and marginal farmers, who own between 1 and 5 acres of land. Around 2.55% of farmers in the Majha and Doaba areas commit suicide. Of these suicides, 1.81% are linked to agricultural debt [5, 21, 22]. The economic condition of small/marginal farmers is quite weak, and they cannot acquire agricultural equipment on their own or via institutional finance. To tide over the situation, custom hiring centers are established for small/marginal landowners to access agricultural equipment [23, 24].

1.2. Issues That Force Farmers to Face Death. Farmers commit suicide to take the extreme step for putting their life to an end for innumerable reasons. Floods, famines, indebtedness, geographical remoteness, loss in productivity, distress sale, inability to pay off debt, and many more factors push farmers to the wall, which often results in suicides. A host of other factors such as illness, climate change, and illogical national policy on agriculture also compel farmers to take resort to suicide. The inability of the farmers to pay off the debts borrowed from the bank/commission agents often acts as a trigger and forces them to end their life [25]. The mismatch between input cost and net profit is so skewed that it frustrates farmers beyond repair, which finally gets culminated in their death. As their revenue goes down, farmers are left with no other alternative except to commit suicide. Of late, the media highlighted the significant spike in

farmers' deaths in Punjab. This unfortunate trend of farmer's suicide is attributed to the restructuring of the agricultural system; crop failure, especially cotton in recent times; mounting debt; and joblessness [26–28]. The media report calls for deep introspection of agriculture-related laws besides looking for other causes that push farmers to the death trap. In order to find out the factors/causes that induce farmers to suicide in Punjab, this research study was performed [29].

1.2.1. Suicide Loss Overview. A check at the agricultural suicide profile revealed that small and marginal farmers with land ownership of up to 5 acres were more prone to suicides. These farmers of the Malwa belt of Punjab [14] would acquire extra land on lease at the cost of Rs 30,000–40,000 per year. These small and marginal farmers accounted for 70%–80% of farmers' suicides in the government records.

In the present era, Farmer's financial burden is increased by routine fixed expenses such as the maintenance and depth of submersible pumps that cost in lakhs. Making such investments is financially unfeasible for a small or marginal farmer, so they borrow from informal sources for which they have to the exorbitant rate of interest (18%–36%). Therefore, in this study, we are going to design an intelligent decision support system. Through this system, the user who wants to give their equipment on a lease can update the data on the framework, and the end-user, who is in search of the tool, can hire the needed tool at the peak season. With this framework, the different farmers who live in provincial zones get updated about the new innovation. Thus, by using them, their crops can be saved from ruins and disasters. This system will help farmers get their crops harvested in peak time without any fear of the nonavailability of equipment. This framework will help the farmers by getting login into the framework and by the accessibility of the needed equipment. Once a farmer gets accessibility to the correct asset, he has to pay the sum for taking the tool on rent/lease for a specific time. In this way, a farmer's dependency on banks/commission agents for borrowing loans will end. This proposed framework, in turn, will enhance the financial strength of farmers [30].

1.2.2. Exploitation by Commission Agent (Arhtiyas). Many farmers with no other income other than agriculture depend on the loan to build farm infrastructure and also to sustain their daily agriculture operations. Since cooperative societies provide short-term official loans for seasonal agricultural needs and do not lend loans for other agriculture-based operations, including loans against leased lands and farmers borrow loans from commission agents. These loans are borrowed at a high rate of interest.

2. Smart Farming Systems

The integration of modern information and communication technologies (ICT) with agriculture, resulting in a Third Green Revolution, is referred to as smart farming. The agricultural world is currently experiencing the Third Green Revolution,

which is based on the integration of ICT solutions such as precision equipment, the internet of things (IoT), sensors and actuators, geo-positioning systems, big data, unmanned aerial vehicles (UAVs and drones), robotics, and other technologies. These changes are necessary for the future of agriculture to enhance productivity and save time [31, 32]. By using remote sensing, the smart farming system saves money, boosts output, and enables better resource management. Constant crop growing in distant areas demands more attention, soil, and water. Because they are linked to smart irrigation and management, which saves time and resources by doing things including testing the pH balance of the soil, analyzing temperature, and finding all the available time, farmers can concentrate on important matters such as pest control, irrigation, and modifying soil conditions. Figure 2 shows the smart farming supply.

Remote data are vital for precision farming, along with computer and equipment mechanization that supports increasing issues and production assistance. In resource management, it is a market approach that balances buyers and sellers [2].

2.1. The Real Purpose of Smart Farming.

Public concern about food safety is on the rise, in part, due to a number of food crises. Clio metrics are used to follow, predict, and guide all stages of the growing and harvesting process for a crop. With the concept of smart farming, the user can get the right equipment at the right time for harvesting the crop to get a better yield. In such systems, networks are more complicated. Many agricultural items are sold using a strategy of reducing costs, which results in low profitability. In this growth, smart data technologies play a key shared role: computers are fitted with all kinds of sensors that provide secure, machine-based data in their environment.

Preharvesting, harvesting, and postharvesting are the three primary categories of agricultural activity. Machine learning technologies have contributed to boosting agricultural gains. Machine learning is a recent technology that is assisting farmers in reducing farming losses by offering detailed crop suggestions and insights. Machine learning is becoming more efficient and accurate because of deep learning algorithms. Using automated machine learning, one may reduce the need for ML expertise while also automating the ML workflow with greater precision [33, 34].

2.2. Machine Learning Techniques.

The following models are the ones that have been implemented in this present work:

(i) Regression
(ii) Clustering
(iii) Instance-based model
(iv) Decision trees

2.2.1. Regression.

This concept comes from supervised machine learning, which can help us predict and explain objects based on categorical data. For example, we can
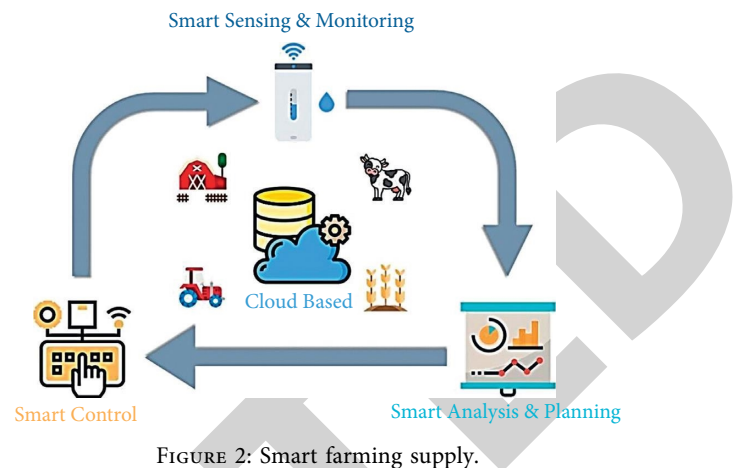

FIGURE 2: Smart farming supply.

predict equipment prices based on the attributes such as type of equipment, location, and demanding days. Figure 3 represents the basic regression plot.

Figure 3 depicts a regression plot where $\frown y1$, $\frown y2$, and $\frown y3$ are the predicted values on a regression line and y1, y2, and y3 are actual values. Here, in the graph in the figure, r1, r2, and r3 are called residual values on the vertical axis and explain the difference between actual and predicted values on the vertical axis [35, 36]. This regression interpretation can perform with various effective algorithms such as simple linear regression, multiple linear regression, polymer linear regression, decision tree, and support vector machine. In Figure 3, a partial regression plot is used in applied statistics to demonstrate the impact of adding another variable to a model that already contains one or more independent variables. Partially regressed plots are also known as additional variable plots, adjusted variable plots, and individual coefficient plots, among other terms.

2.2.2. Clustering.

It is an unsupervised learning technique. This technique does not have any output information for the training process [37]. Clusters can organize a bunch of data based on the different clusters. Clustering starts with a data point, and these data points can be measured like length and width. Clustering is used to create a group of data that is called clusters. The clustering happens fully automatically.

Clustering is the process of separating a population or set of data sets into a number of groups such that data points belonging to the same group are more identical to one another and different from data sets belonging to other groups. It is essentially a collection of items based on their similarity and dissimilarity [38–40]. Figure 4 demonstrates that the system has a large number of data set in the form of clusters. Content-based clusters will be formed automatically using our technology. For instance, in the scenario of renting and sharing agricultural equipment, our system would get the user's current position from the whole India map. In the current study, we have implemented Google API, which identifies the location of the equipment to be hired. Clustering is critical as it implies the fundamental classification among data sets. Clustering is totally
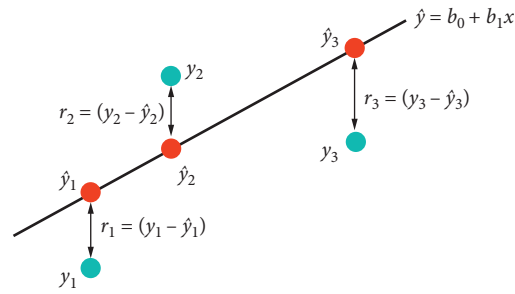
$$\hat{y} = b_0 + b_1 x$$

FIGURE 3: Regression plot.
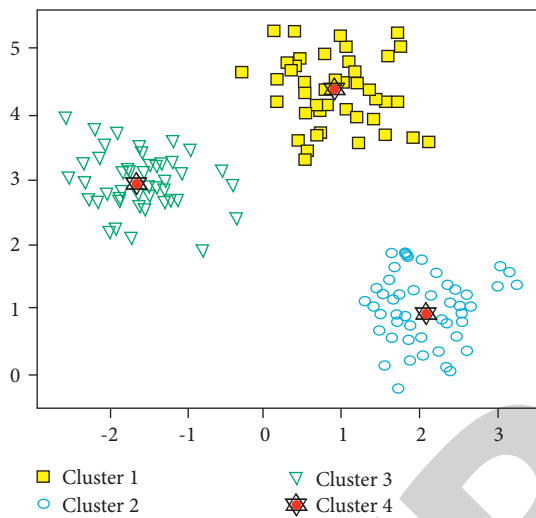

Cluster 1   Cluster 3
Cluster 2   Cluster 4

FIGURE 4: Clusters in the scattered plot.

subjective. It depends on the consumer what criterion satisfies their requirements. An example of this would be: we may be interested in identifying representatives for homogenous groups (data reduction), as well as discovering "natural clusters" and describing their previously unknown attributes. This method makes hypotheses that will provide clusters of points with varying validity.

2.2.3. Decision Trees. A decision tree is one of the best modeling techniques used in machine learning. It is one of the predictive modeling approaches used in machine learning w; here, the data is continuously split according to the particular parameters, namely, decision nodes and leaves. These are the basic fundamental steps to explain this tree. The leaves represent the final outcomes, and the decision nodes represent the points at which the data is split [41, 42]. Training data may be used for both regression tasks but is mostly employed for addressing classification issues. Figure 5 depicts a representation of the decision tree. An internal node represents a data set feature; a branch represents a rule base; and each leaf node represents a result. A decision tree has two nodes: a decision node and a leaf node. Selection nodes serve to make any decision, while leaf nodes act as the results of such choices. The judgments of the tests are based primarily mostly on the data set's characteristics.

2.2.4. Instance-Based Model. Instance-based means building hypotheses directly from training samples. It is a memory-based model that can compare trained instances with the new problem instance. One of the most important advantages of this based model on the other methods is the unseen data can be easily adapted by this model, that is, it is a memory-based model; it may simply store the new instance. This model is exactly linked with the renting and sharing of the equipment, that is, how this system can get the information about the number of equipment used by the user in the past years.

2.2.5. Artificial Neural Network. Artificial neural networks are machine learning algorithms that simulate the human brain. As stated above, the neurons in our nervous system can learn from history; in the same way, the ANN is capable of learning from the data to produce forecasts or categories. ANNs are time-varying mathematical methods that discover a new sequence in complex relationships between outputs and inputs [43]. Neural network networks are commonly used in tasks such as machine vision, voice recognition, text mining, and diagnosis. Because ANNs learn from illustration data sets, they have a major advantage. Most commonly, the ANN is discrete structure estimation. With these tools, it is possible to arrive at distribution solutions at a cost-effective rate. ANN is also capable of taking a data set and returning the final output. ANNs can improve current statistical tools due to their advanced meaningful insights.

3. Research Methodology

3.1. Data Collection. Farmer fluctuations are driven by a multitude of factors that primarily include educational qualifications, age, yearly income, spending, the number of family members, lack of technical expertise, the load of debts, and many other contributing factors.

The foregoing concerns contributed to the demise of farming in India. Considering this issue, in this present study, a socioeconomic study is undertaken in Punjab, and a technical solution is found to encourage agricultural equipment rental and sharing. This chapter includes methods and methodology used for the development of the Internet-based smart agricultural resource sharing framework. The purpose of this research is to modify the farming production in Punjab. For this, recent supplementary data has been gathered and interpreted from a wide range of
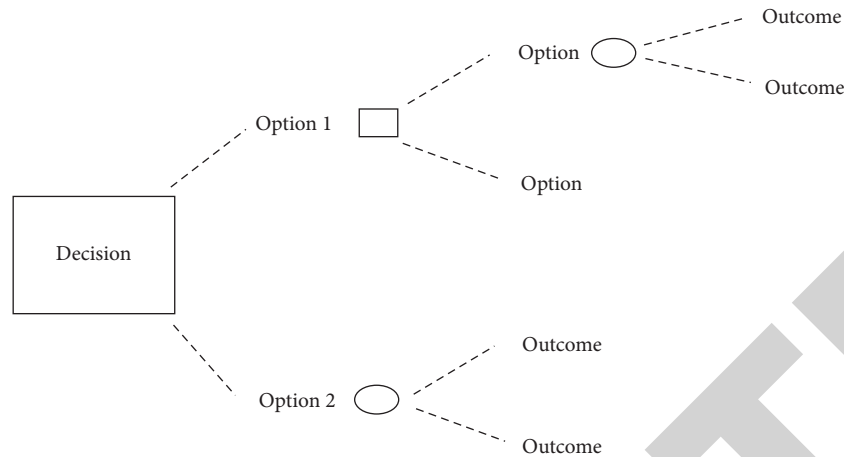
FIGURE 5: Representation of decision tree.

sources. In this applied research, we gathered the data from 562 farmers in Punjab from different districts, villages of Majha, Malwa, and Doaba regions of Punjab. The data has been collected by an open-end questionnaire, which includes various parameters as shown in Table 1. The questionnaire was created in English and Punjabi languages taking into concern the education level of the farmers. The purpose of this collected data is to explore the major concerns faced by the farmers. By the parameters loan source, the purpose of debt, interested to hire manufacturing tools, and interested in mobile application, we anticipated the need for renting and sharing of the equipment.

To know the financial and educational situation of farmers in Punjab, a survey was done using Google Forms as well as door-to-door questioning. Table 1 shows the study from the sample count of 562 farmers from Majha district of Punjab shows that most of the farmers are having small to moderate landholdings and the farmers are not educated enough to know the latest techniques or latest farming mechanization that can help them get more revenue from the same farming land. Table 2 depicts the details of the type of farmers.

Manually obtained data infers the need for rental and sharing of equipment. It includes several contributing aspects such as they are drowning in debt, ignorance of technical options, and government regulations. Therefore, during the harvesting period, they are unable to use the equipment owing to its high demand. Farming operations also rely on a lot of bank loans and financial support. Financial inclusion is critical for farmers. The financial inclusion gap for India's farmers remains persistent, despite several initiatives. Most farmers commit suicide due to their financial load, which is further aggravated by various indirect factors. Banking facilities are tough to get for small and marginal farmers. As mechanization, as well as the underutilization tendency, raise production costs or reduce net returns to farmers, farming becomes expensive.

Equipment is costly to purchase and maintain, and over that, the loan's monthly/yearly EMI adds on. A farming equipment rental for agriculture aims to provide small farmers who cannot afford to buy costly machinery with access to modern technology. It will increase farmer income through increasing productivity by farm mechanization. Farmers will not have to purchase tractors or other vehicles because they will be available for rent at a fraction of the cost of ownership.

Farmers who cannot afford to buy high-end agricultural machinery and equipment can hire farm equipment and machinery from custom hiring centers. A custom hiring center is an effective mechanism for most small farmers to gain access to agricultural machinery services. In custom hiring, farmers do not have to worry about start-ups costs or repair and maintenance costs. They only pay for chargeable services and personalized service prices. Literature reported that the custom hiring centers have the potential application for renting and sharing of equipment.

After reviewing the many challenges encountered by farmers, we have built a support structure the smart tillage that helps farmers rent and share equipment. For this renting sharing of equipment, we have implemented the concept in Python language. The systematic steps to establish the information management system are implemented by artificial intelligence and machine learning algorithms. The classification of machine learning falls into different categories such as linear regression, instance-based model, clustering, decision tree, and many more. We have developed a model that embeds the decision tree, which would provide the ideal solution for farmers. Decision trees are helpful because they require us to think about all conceivable outcomes and follow each route to a conclusion. It gathers and analyzes information across the branches to identify decision nodes for additional study.

3.2. Machine Learning Workflow. To assess the data set from the selected smart tillage, we employed multiple classifiers such as logistic regression, k-neighbors, and decision tree. The trained model's accuracy was projected using data from 562 farmers polled. Our training data set has 447 observations, whereas our testing data set contains 115 observations. The model in Figure 6 utilizes farmer data as input, in which many criteria including land, gain from farming,

TABLE 1: Snapshot of sample collected data set.

1	2	3	4	5	6	7	8	9	10	11	12
Name	Village	Land	Age	Gender	Education	Family members	Per month expense	Agriculture experience	Farmer category	Farm registered or not	Aware of new farming tools
Buta Singh	Banger Muhabat Singh, Bathinda	3 acre	38	Male	Graduate	4	10,000–25,000	18	Small	No	Yes
Gurdev Singh	Banger Muhabat Singh, Bathinda	1 acre	40	Male	Secondary	4	10,000–25,000	20	Small	No	No
Gurjant Singh	Banger Muhabat Singh, Bathinda	2 acres	39	Male	Secondary	6	25,000–50,000	19	Small	No	No
Mahinder Singh	Banger Muhabat Singh, Bathinda	3 acres	44	Male	Secondary	5	25,000–50,000	24	Small	No	Yes
Mejor singh	Banger Muhabat Singh, Bathinda	3 acres	48	Male	Secondary	6	25,000–50,000	28	Small	No	Yes
Parminder Singh	Banger Muhabat Singh, Bathinda	6 acres	55	Male	Secondary	5	25,000–50,000	35	Medium	No	Yes
Gurtek Singh	Banger Muhabat Singh, Bathinda	5 acres	60	Male	Graduate	5	25,000–50,000	40	Medium	No	Yes
Rajinder Singh	Banger Muhabat Singh, Bathinda	5 acres	39	Male	Secondary	4	10,000–25,000	19	Medium	No	Yes

TABLE 2: Detail of type of farmers.

Sl. No.	Type of farmers	Percentage (%)
2	Small	67.06
3	Moderate	31.08
4	Large	1.06

per month expenditure, awareness of new technologies, availability of loans, usage of smartphones, and information on interested users are examined. In this, the comparison is done with the following three techniques:

   (i) Logistic regression
   (ii) K-neighbors classifier
   (iii) Decision tree

In order to view the number of farmers/users who are interested to hire manufacturing tools. From the selected smart tillage, we have tested the data set by different classifiers named logistic regression, k-neighbors, and decision tree. Herein, surveyed data of 562 farmers have been used to predict the accuracy of the trained model. Our training data set consists of 447 observations, and the testing data set consists of 115 observations. We input the trained data set into the model and trained the model, and then we get the predication for test and trained data sets. This model would improve quality of life by bringing them together for win-win trades. Farmers can gain some extra cash without much effort by simply posting items that are no longer in use, giving them the opportunity to find equipment at reasonable prices. The steps for the proposed model are given in algorithm 1 are as follows:

   Step 1: inputting the farmers' data into the system
   Step 2: dropping the duplicate columns
   Step 3: understanding the target variables
   Step 4: initializing and fitting the model
   Step 5: predicting the values of test data
   Step 6: preparing classification reports
   Step 7: evaluating model
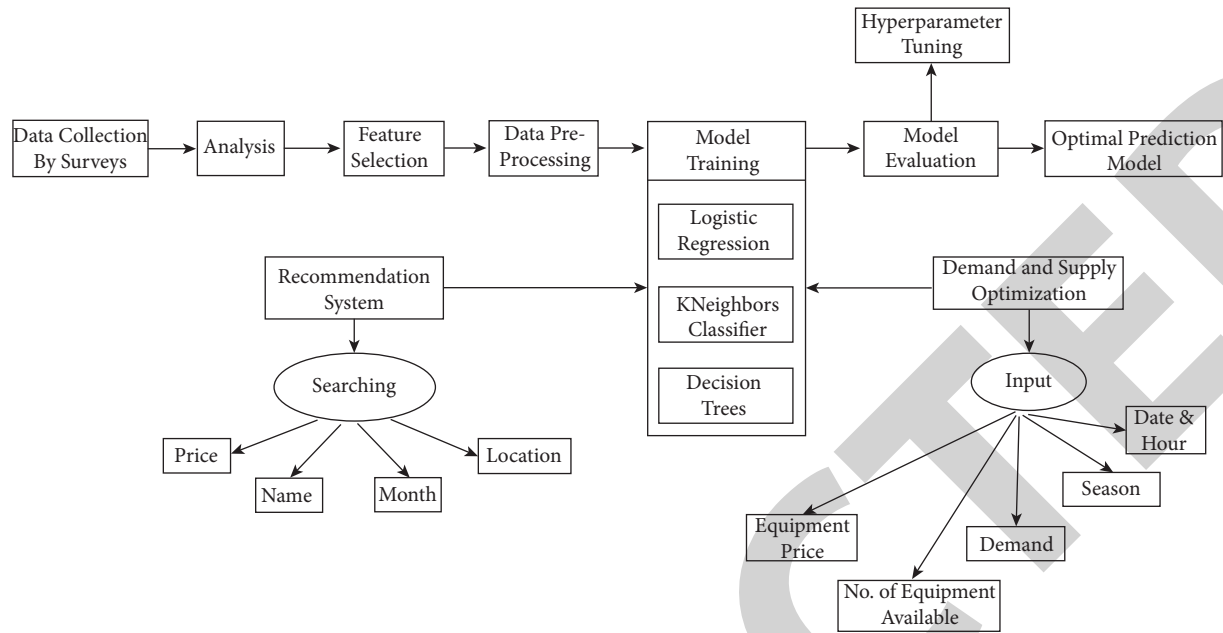   Step 8: depicting accuracy

Figure 6: Accuracy model.

3.2.1. Step-by-Step Procedure: Smart Tillage. In terms of the procedure, only users who have been granted permission by the system administrator are permitted to rent or hire their equipment. The user who wants to hire equipment must submit the necessary information in the form of a picture of the equipment, the distance for which it may be leased, and the fee per day for leasing the unit. As soon as the data is submitted by the user, it will be cross-checked by the system's administrator before being made accessible in the client and search lists. The customer is responsible for uploading all of the properties that the client wishes to have listed for hire or rental. The smart tillage is shown in Figure 7 as a layout.

The client after selecting the location through Google Maps' longitude and latitude will be able to search for the equipment using filters. From the displayed list, the client who wants to hire the equipment selects the product and clicks on it; it will pop up showing all the details such as cost of hiring, available for how many days. If it matches with the requirement of the client, he will have to select the hiring dates from the day he wants to hire and till the day it will be hired for. Once the days are fixed for hiring, the system will display the total rent it will cost. The client then has to send a request to the admin for authentication. It will be listed on the client dashboard only after the admin approves the request. Along with this, the equipment will be removed from the main search list for other clients for the same equipment for the same dates. In Figure 8, the system is having password-based security. Only those users who are having an account in this system can access and update details of their own profile only. There are number of parameters used for the filtration of data such as location, distance, cost per day, and number of days. Machine learning is employed to determine the location, pricing information, and number of days the equipment is rented

for. Search is done via a database in order to locate a machine matching the specifications set by the customers. The cost per day is fixed, which will be invoiced after computing the cost for the number of days specified using the calendar function to and from filters. The model was built using machine learning for data Interpretation and report production. Table 3 shows the methodology/tools/instruments to be used.

3.3. Client Approach. Figure 9 represents the systematic approach for renting equipment. The client here can rent and hire the equipment. The client once gets registered will upload the equipment details using the name, dates for displaying in the search list, cost per day, and image of the product. Once the details are filled the request will be submitted. When it gets approved by the admin, the product will be shown on the client dashboard, and a message will be received by the client.

3.4. Location Prediction Approach. This is the step where the system identifies the location using Google Maps' longitude and latitude clicked by the users logged in to the system, searches the locations within the range selected by the user, and displays the list of results. Figure 10 depicts the location prediction approach used in the system. We have incorporated the Google Astro Library and OpenLayer Map, which reveals the current location of the user.

3.5. Distance and Cost Predication Approach. The distance here is used for search and distance of client who is hiring the rented equipment. It will allow the client to have a cost variation that depends on the distance from where the equipment is hired. Normally distance parameter is used to

```
INPUT: S, where S = set of classified instances
OUTPUT: decision tree
Require: S ≠ Φ, num_attributes >0
(1) Procedure BUILD TREE
(2) Repeat
(3) maxGain < - 0
(4) Split A < - null
(5) e < - Entropy(Attributes)
(6) For all attributes a in S do
(7) Gain < - Information Gain (a, e)
(8) If gain > maxGain then
(9) maxGain < - gain
(10) splitA < - a
(11) End if
(12) End for
(13) Partition (S, split A)
(14) until all partitions processed
(15) End procedure
```
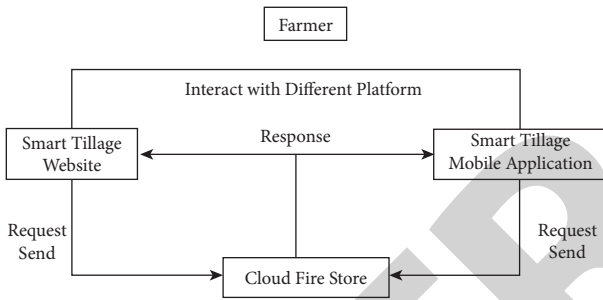
ALGORITHM 1: Decision tree.

FIGURE 7: Layout of smart tillage framework.

display all the clients who are offering the required product. Figure 11 predicts the distance and cost approach. To utilize the equipment; one must search the tool by product name, price, month, and location. Caching will occur if he is in the exploring module. The user will be recommended by the product via a content-based recommendation system. When the user goes to the booking module, he will get his first and final hiring dates. The total cost includes the equipment cost and the travelling cost.

The emphasis of the study was on specific aspects of the proposed method. The very first step is to collect information, and the second is to incorporate it into the process. The technical points in the first section of the report detailed the characteristics of 562 farmers from various Punjab regions, as well as their interpretation based on various categories. The information gathered from actual farmers has been organized.

The whole application would allow the development of a method for determining farmer expectations and demands for resource sharing and the rental of agricultural equipment and machinery. The steps for building a knowledge network that combines artificial intelligence and machine learning in a standardized manner.
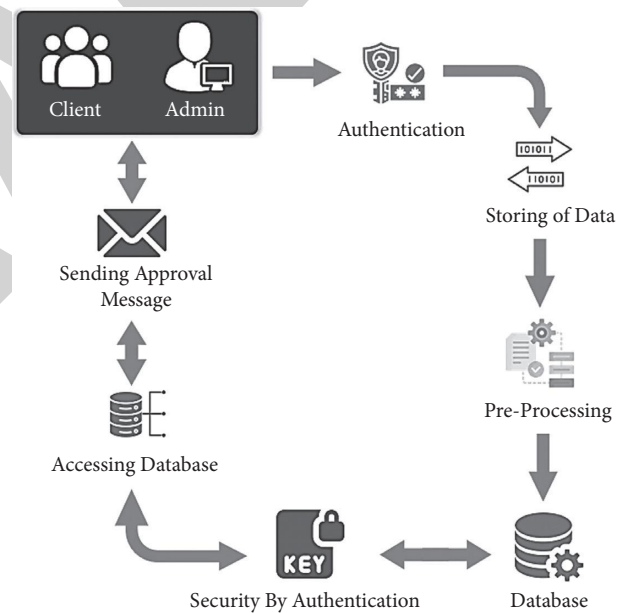

FIGURE 8: Flow chart of the proposed approach.

4. Results and Discussion

In order to analyze the data, the farmers are divided into three types: small, moderate, and large. Of the total 562 farmers, 377 farmers fall under the type of small farmers; 179 fall under the type of moderate, and 6 farmers fall under the large farmers type.

The main issue of the farmers is that they are not sensitized with modern equipment and tools, and on the flip side, they are falling under the burden of debt that forces them to commit suicide. In order to resolve this concern of the farmers, we have developed a uberized model that deals with the renting and sharing of farming equipment. So, in

TABLE 3: Methodology/tools/instruments to be used.

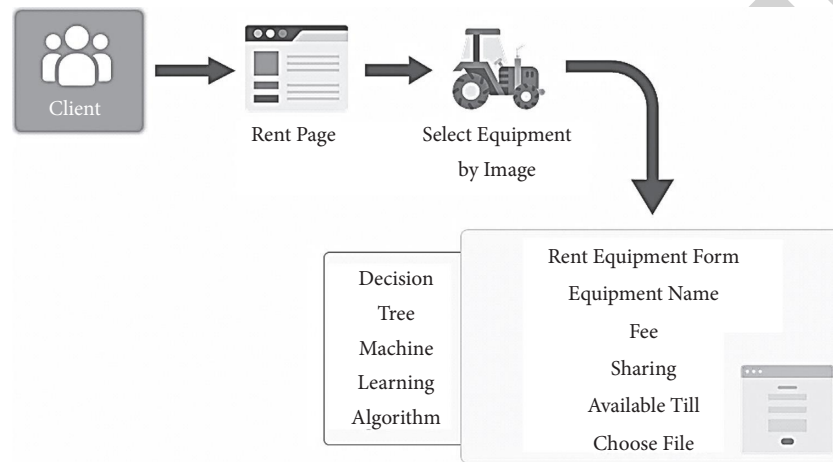| Objective	Sample size (number of participants)	Instrument/tool/sample design, etc. to be used
1	562	Primary data collection, Google Form
2	Smart tillage framework	(i) HTML language (ii) CSS language (iii) Django framework (iv) Python 3.7 (v) Machine learning
3	Smart tillage mobile application	

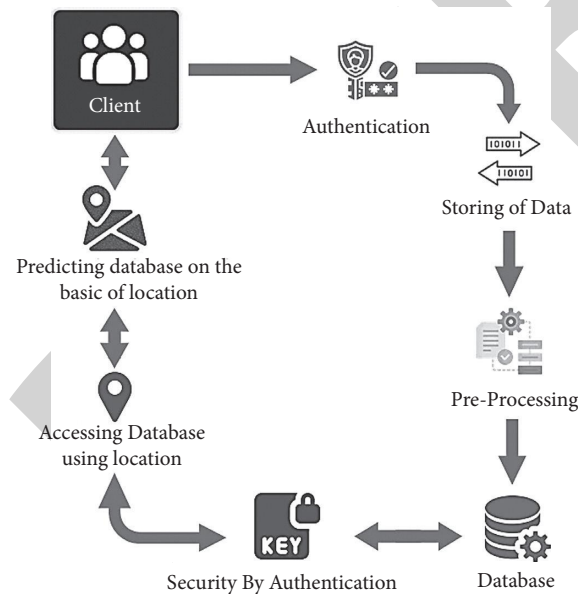

FIGURE 9: Systematic approach for renting equipment.

FIGURE 10: Location prediction approach.

order to run this uberized model, our first concern is to find how many farmers have their own smartphone. Table 4 represents the out of these collected information: in case of small type out of 377 farmers, 155 farmers have smartphones: out of total 177 moderate farmers, 144 have smartphones; and out of 6 large farmers, 5 large farmers have their smartphones. Figure 12 depicts the plot of

Interpretation of farmer's type with interest in the mobile application.

Out of these, all the small farmers, that is, 377 and 178 moderate and 1 large farmer are interested in smartphones. The concept of this parameter selection is reached to the view of a custom hiring system so that farmers can rent and hire their equipment accordingly.

4.1. Basic Information. 4.2. Monthly Expense of Ranchers and Their Productivity from Agriculture. Figure 13 depicts the comparison of small, moderate, and large farmers on the basis of their expenses, count, gain from farming, and number of agriculturists. Table 5 represents all types of farmers who experienced their monthly expenditures in the range of 10,000–25,000, 25,000–50,000, and more than 50,000. These expenses are labelled as A, B, and C under the three different types: small, moderate, and large. For label A, 146 farmers fall in the small; 56 fall in the moderate; and 3 farmers fall under the type of large farmers. For label B, 225 fall in the small; 120 fall in the moderate; and 3 farmers fall under the large type. Similarly, in the case of C, 6 fall under the small; 3 fall under the moderate; and no farmer lies under the large type. However, the next part of Table 5 represents farmer's type with gain from farming and their number of counts. In order to consider this gain from farming is categorized into three groups: 50,000–2,00,000, 2,00,000–5,00,000, and more than 5,00,000. This income from agriculture is labelled as D, E, and F. In the case of label D, 377, 19, and 1 farmers lie in the small, moderate, and large
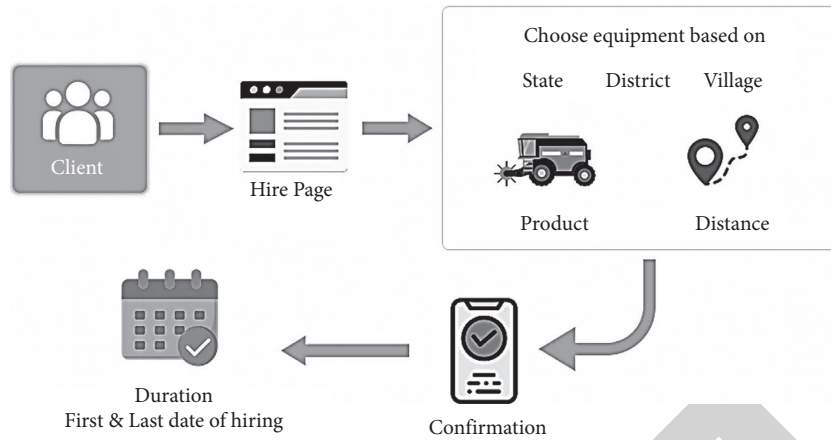
Figure 11: Distance and cost approach.

Table 4: Type of farmers interested in mobile apps and smartphones.

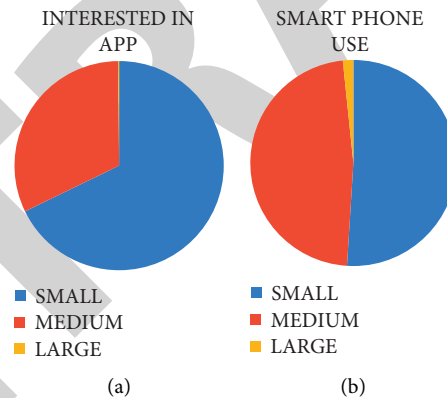| Farmer group interested in mobile application		Farmers using smartphone	
Type of farmers	Interested in app	Type of farmers	Mobile use
Small	376	Small	145
Moderate	177	Moderate	144
Big	1	Big	5

Figure 12: Interpretation of type of farmers versus interested in mobile app.

types, respectively. For the label E, 1, 159, and 0 farmers fall in the small, moderate, and large types. For the label, 0, 1, and 5 farmers fall in the small, moderate, and large types.

4.3. Interpretation between Type of Farmers, Debt Cause, and Their Interest to Hire Manufacturing Tools.
Table 6 depicts based on the three categories of the farmers: small, moderate, and large. Out of these all categories, some of the farmers are interested in loans, while others are not. Loan is one of the main causes that force the farmers to commit suicide. From this mentioned interpretation, this inference depicts that the maximum farmers from different categories have taken loans to buy the latest tools. This survey reached the result that farmers are under the burden of loans due to the following reasons:

 (i) Plantation and fertilization
 (ii) Latest tools
(iii) Buying land
(iv) Education

Figure 14 represents that out of 377 small farmers, 179 are interested in loans, 198 are not interested in loans, and all 179 are interested in hiring machinery. In the moderate type, out of 179 farmers, 53 are availing loan, and all are interested in custom hiring; others 126 are not interested in loans, and 121 are interested in hiring machinery. Of the large type of farmers, out of 6, 4 farmers are interested in loans, and all are interested in hiring machinery, and the other 2 do not want to avail the loan, but they are interested in hiring machinery. Figure 14 also depicts the debt caused for the farmers. This
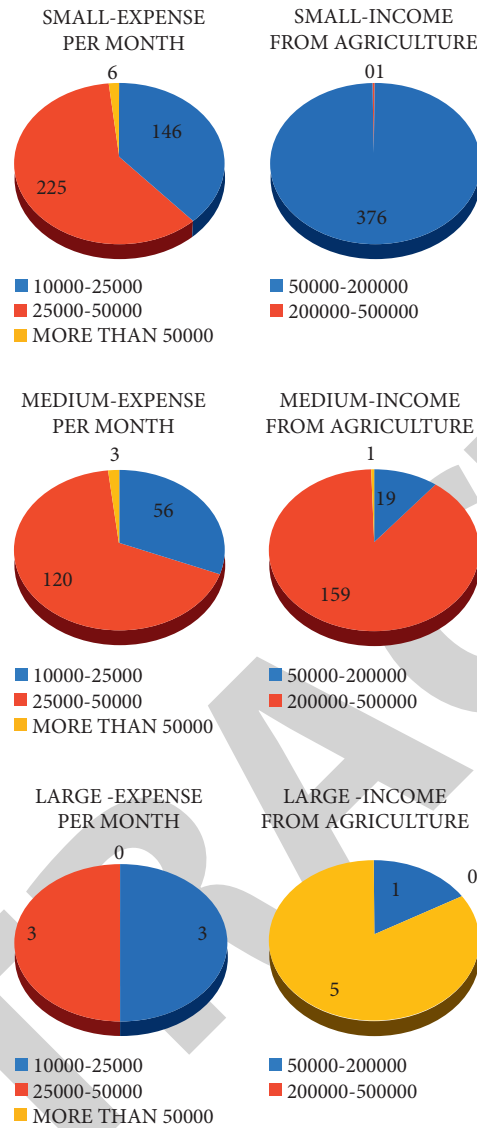
SMALL-EXPENSE
PER MONTH

- 10000-25000
- 25000-50000
- MORE THAN 50000

SMALL-INCOME
FROM AGRICULTURE

- 50000-200000
- 200000-500000

MEDIUM-EXPENSE
PER MONTH

- 10000-25000
- 25000-50000
- MORE THAN 50000

MEDIUM-INCOME
FROM AGRICULTURE

- 50000-200000
- 200000-500000

LARGE -EXPENSE
PER MONTH

- 10000-25000
- 25000-50000
- MORE THAN 50000

LARGE -INCOME
FROM AGRICULTURE

- 50000-200000
- 200000-500000

Figure 13: Farmers type versus expenses per month and gain from farming.

Table 5: Expense of ranchers and their productivity.

Type of farmers	Monthly expenditure	Number of agriculturist	Gain from farming	Number of agriculturist
Small	10,000–25,000	146	50,000–200,000	376
	25,000–50,000	225	200,000–500,000	1
	More than 50,000	6	More than 500,000	0
Moderate	10,000–25,000	56	50,000–200,000	19
	25,000–50,000	120	200,000–500,000	159
	More than 50,000	3	More than 500,000	1
Large	10,000–25,000	3	50,000–200,000	1
	25,000–50,000	3	200,000–500,000	0
	More than 50,000	0	More than 500,000	5

interpretation reached up to the mark that this is the reason why farmers are under suicide.

4.4. Feature Selection. The overview of the data has been represented in Figure 15 that tells us about mean, standard deviation, and minimum and maximum value of the collected data set of 562 farmers. The average value is represented by mean, and the standard deviation is used to find the difference in value and the other range of values are represented by maximum and minimum.

The association between knowledge of new technologies and agricultural experience is seen in Figure 16. To facilitate this, farmers are classified into three categories: small,

TABLE 6: Interpretation between the type of farmers and they availed loan or not with reason and their interest to hire manufacturing tools.

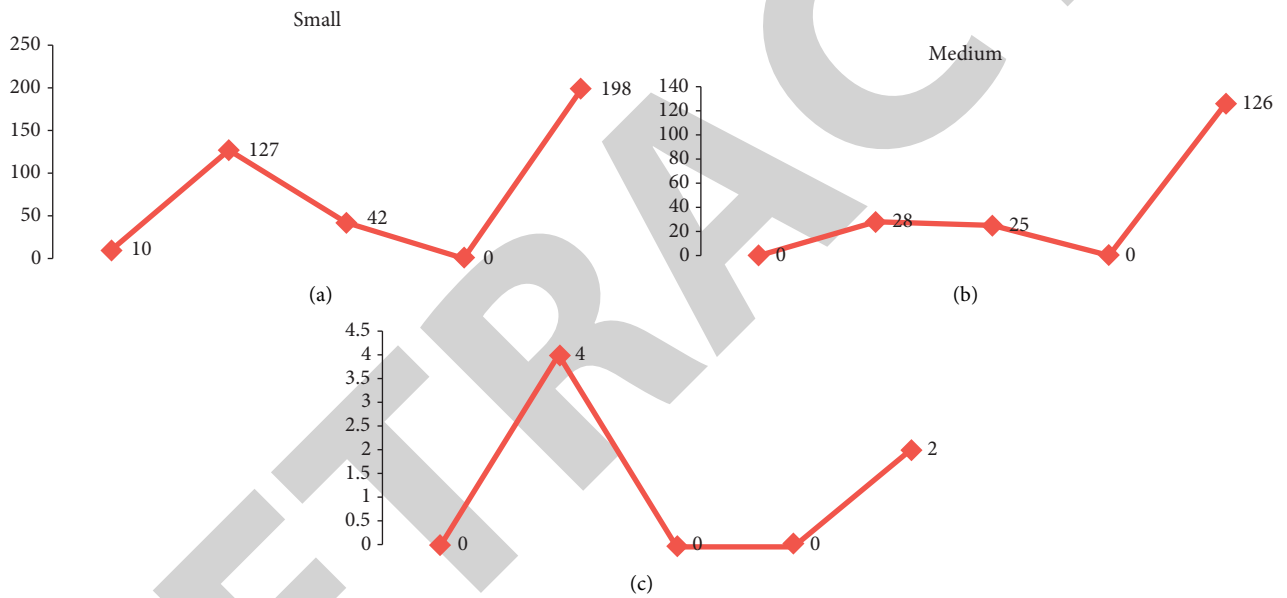| Type of farmers	Availed loan or not	Purpose of debt	Count of reason	Interest to hire manufacturing tools.
Small = 377	Yes = 179	New seeds	10	179
		Latest tools	127	
		Buying land	42	
		Education	0	
	No = 198	No debt	198	197
Moderate = 179	Yes = 53	New seeds	0	51
		Latest tools	28	
		Buying land	25	
		Education	0	
	No = 126	No debt	126	121
Large = 6	Yes = 4	New seeds	0	2
		Latest tools	4	
		Buying land	0	
		Education	0	
	No = 2	No debt	2	2

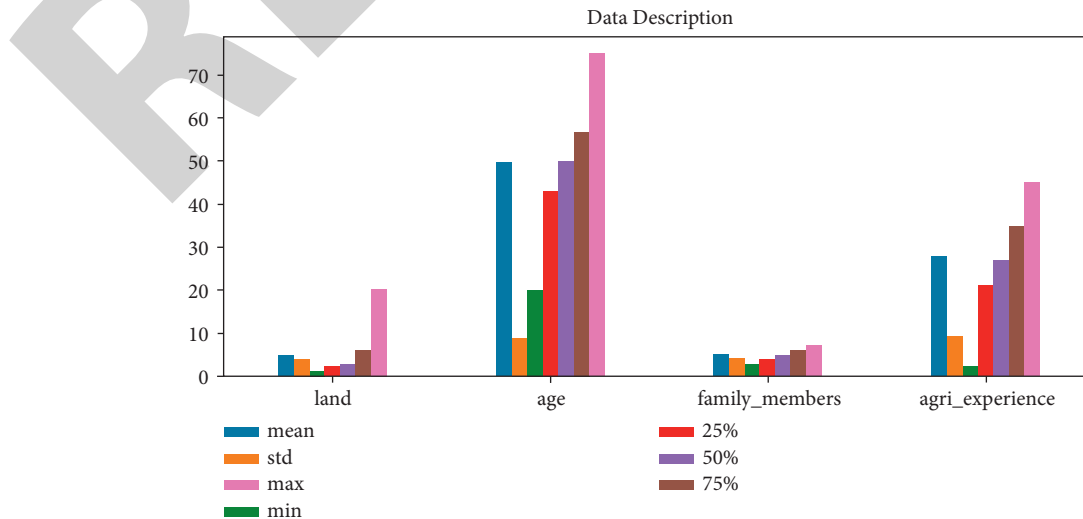FIGURE 14: Relationship between the type of farmers and their reason and interest to hire manufacturing tools.

FIGURE 15: Overview of collected data.
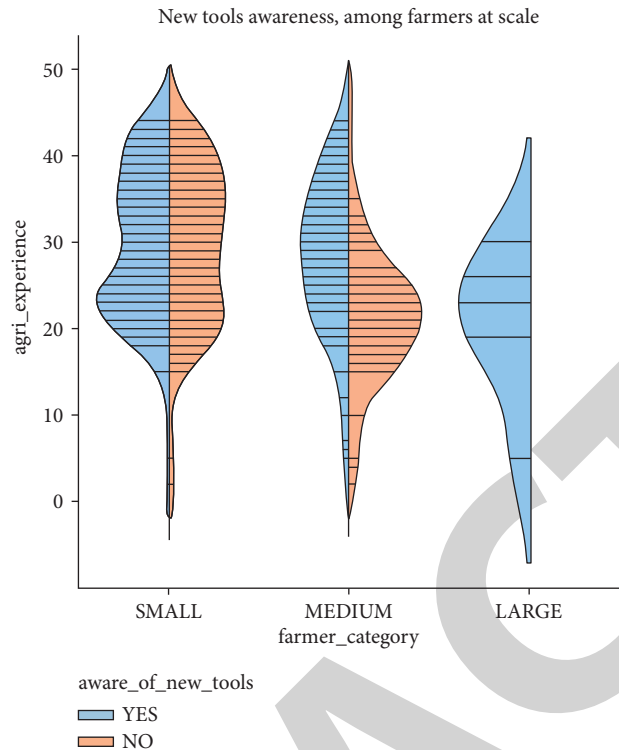
New tools awareness, among farmers at scale

Figure 16: New tools awareness with farmers' type.

moderate, and large. This result indicates that small farmers, despite their increased agricultural expertise, are still unaware of farming implements. It is used to represent symmetrical data. However, as their agricultural expertise grows, they become more conscious of new instruments. Large farmers type includes that with the age of agriculture experiences, all the farmers have the awareness of new tools.

The relationship between two variables is measured by correlation, which is a statistical term that quantifies how linearly related two variables are (meaning they change together at a constant rate). In the world of correlation, there are two kinds. Both a positive and a negative association may be found. In the case of positive correlation, the rise in dependent parameters will result in an increase in the independent parameters as well, but in the case of negative correlation, the increase in dependent parameters will result in a drop in the independent parameters. When the correlation coefficient is between +1 and −1, it is referred to have a high correlation coefficient. This matrix depicts the relationship between family members who were born on land and those who have agricultural experience. The first row (land) in Figure 17 illustrates the best association between agricultural experience and land, and no correlation is identified between land and family members.

Figure 17: Agriculture experience and land correlation.

When it comes to ages, row 2 displays the best association with agricultural experience and vice versa. According to the land, the third-row family member has the greatest relationship with it.

Figure 17 shows the association between the interest in machinery and mobile application. Totally 95.7% of the

farmers want to hire equipment, while 96.4% want to use a mobile application. We discovered a correlation between these two variables, which is that farmers who wish to hire equipment are particularly interested in mobile applications.

4.5. Comparative Interpretation of the Machine Learning Algorithm.
Three machine learning classifiers are used for the interpretation: logistic regression, k-neighbors classifiers, and a decision tree. This research indicates how many farmers would want to use our technology. To summarize, the model was trained using training data that included 446 observations and then was tested on a test data set of 116 farmers. By using the decision tree, we are obtaining the highest accuracy of the model from our test observations of 116 people. Figure 18 depicts the comparative analysis by different classifiers models. The formula to calculate accuracy is as follows.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{1}$$

where TP, FN, FP, and TN represent the number of true positives, false negatives, false positives, and true negatives, respectively.

Logistic regression: out of 5 negative predictions, the model gave 1 false positive, and out of 111 positive predictions got all of them correct.

K-neighbors classifier: out of 5 negative and 111 positive predictions, this model got all of them correct.

Decision tree classifier: out of 5 negative and 111 positive predictions, our tree model got all predictions correct.
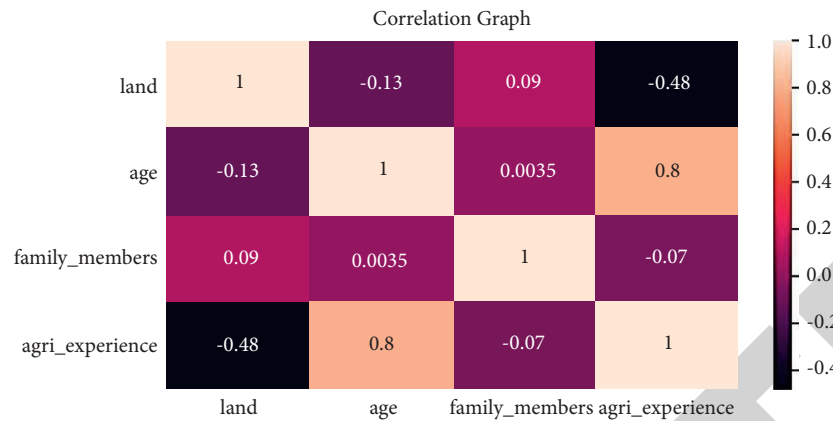
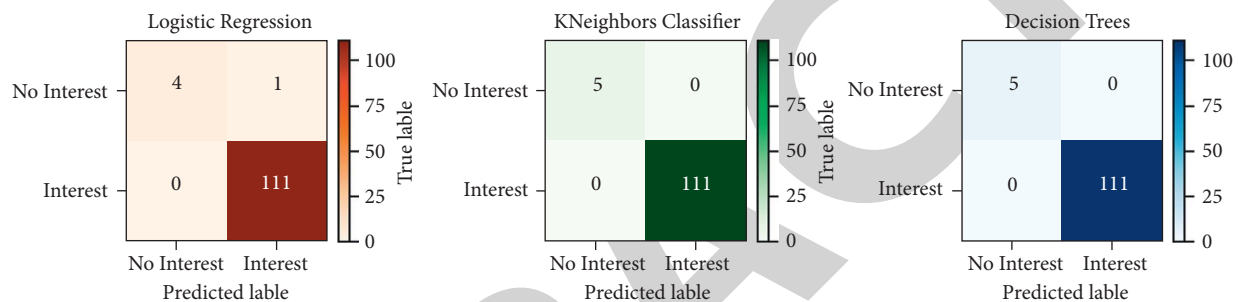Figure 17: Correlation graph of land with different parameters.

Figure 18: Comparative interpretation by different classifier models.

After performing classification with different models such as logistic regression, k-neighbors classifier, and decision tree, it is found that decision trees and k-neighbors were the better performers; we have chosen decision trees as our model of choice because of it being a nondistance-based algorithm, its white-box approach, and excellent performance on our data set.

5. Conclusion

This research polled 562 Punjabi farmers. The poll revealed many critical findings, including why farmers are not harvesting more. The difficulties confronting agriculture were examined in terms of farmer education, land ownership, awareness, mobile phone use, debt burden, loan source, and interest in renting equipment. The research found that farmers lack awareness of current technology, which is extensively used in agricultural operations worldwide. Another barrier is the financial status of farmers, especially small and marginal farms. Farm management loans from commission agents or private firms progressively enslave the farmers. Landlords continue to adopt traditional manufacturing methods despite their ignorance of current production methods. This project developed smart tillage, a platform that enables farmers to rent and lease equipment. The study also built a machine learning model. Decision trees are ideal for machine learning and tool and equipment hiring. It also tries to improve farmers' quality of life by decreasing labor-intensive tasks. This thesis focuses on smart farming via equipment sharing and leasing. The proposed

tasks employing various machine learning techniques were developed as a result of exploratory and highly experimental work; future work is expected to include new experiments and tasks that exploit other sensor types and data sets, as well as related method and result optimization, in order to meet the great heterogeneity of agriculture companies and the hardware sensor market.

Data Availability

The data used are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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