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How Machine Learning is Redefining Agricultural Sciences: An Approach to Predict Apple Crop Production of Kashmir Province

Sheikh Amir Fayaz[1], Nishit Kaul[2], Sameer Kaul[1], Majid Zaman[3*], Waseem Jeelani Baskhi[1]

[1] Department of Computer Sciences, University of Kashmir, J&K, Srinagar 190006, India
[2] Deptt. Computer Science and Electrical Engineering, Massachusetts Institute of Technology, 77 Massachusetts Ave, Cambridge, MA 02139, USA
[3] Directorate of IT&SS, University of Kashmir, J&K, Srinagar 190006, India

Corresponding Author Email: zamanmajid@gmail.com

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ABSTRACT

One of the earliest and most popular (and effective) machine learning methods is decision trees. Different decision tree changes have been suggested and put into practice over time. Selecting the model that best fits the situation is essential while examining the data. Numerous classification and regression specialists have suggested ensemble tactics for tabular data as well as diverse methods for solving classification and regression issues. In this study, the raw historical apple crop dataset is transformed into a discrete dataset using the Gini Index and information gain. On the resulting discrete dataset, the decision tree algorithm is used. Information Gain is determined for each attribute, and the attribute with the highest information gain is used as the splitting node, which is then applied recursively. With an accuracy of 84.54%, the decision tree algorithm used predicts the apple yield in Kashmir province. Later, a comparison between the accuracy of decision tree and other algorithms has also been made and it was observed that the decision tree performed better in accuracy and other statistics than all the other implemented algorithms.

1. INTRODUCTION

Data mining, also known as knowledge discovery in databases, is the process of discovering patterns and relationships in large datasets. These patterns and relationships can be used to make predictions about future outcomes or to identify important factors that may impact the success of a particular task. In the field of agriculture, data mining techniques have been used to predict crop yields and identify factors that may impact the success of a crop. One such crop is apples, which are a major commodity in many parts of the world [1]. The production of apples involves various factors such as weather conditions, soil quality, and pest and disease management. Accurate predictions of apple production are important for farmers, as they can help inform decisions about planting, fertilization, and pest management [2]. Additionally, accurate predictions of apple production can help governments and businesses to plan for market demand and supply.

Over the years, various data mining techniques [3-5] have been used to predict apple production, including decision trees, support vector machines, and artificial neural networks. In this introduction, we will provide an overview of these techniques and discuss their strengths and limitations in the context of predicting apple production.

Traditional approaches in machine learning, including decision trees, are typically characterized by their simplicity, interpretability, and ease of use. They often rely on a set of rules or decision boundaries that can be easily visualized and understood, making them popular in fields such as medicine and finance where interpretability is essential.

Decision trees are a popular traditional machine learning method due to their ability to handle both categorical and continuous data, and their ability to handle missing values. However, decision trees can suffer from overfitting, where the tree becomes too complex and captures noise in the data.

Decision trees are a type of data mining technique that involves the use of a tree-like model to make decisions based on the available data. The tree consists of nodes and branches, with each node representing a decision or attribute and each branch representing the possible outcomes of that decision or attribute. Decision trees are effective for predicting apple production because they allow for the identification of important factors and the ability to make predictions based on those factors [6]. One limitation of decision trees is that they can be prone to overfitting [7], which occurs when the model is too complex and is able to fit the training data perfectly, but performs poorly on new data. Overfitting can be mitigated by pruning the tree or using techniques such as cross-validation to evaluate the performance of the model on new data. Support vector machines (SVMs) are a type of data mining algorithm that uses a linear function to separate data points into different categories. SVMs are particularly useful for predicting apple production because they can handle large amounts of data and can accurately classify data points even when the data is not linearly separable. However, one limitation of SVMs is that they can be sensitive to the choice of kernel function, which determines the shape of the decision boundary [8]. In addition, SVMs can be computationally intensive, which can make them difficult to scale to large datasets. Artificial neural networks (ANNs) are a type of machine learning algorithm that is inspired by the structure and function of the human brain. ANNs are particularly useful for predicting apple production because they are able to learn from the data and make predictions based on patterns and relationships identified in the data. However, ANNs can be prone to overfitting if they are not properly designed or trained, and they can also be difficult to interpret due to their complex structure. In addition, ANNs can be computationally intensive and require a large amount of data to train effectively [9-11].

In conclusion, the use of data mining techniques for the prediction of apple production has proven to be effective in identifying important factors and making accurate predictions. However, it is important to carefully evaluate the strengths and limitations of each technique and choose the one that is most appropriate for the specific data and prediction task at hand. In this study, we applied both conventional and ensemble methods (Decision trees, naive Bayes, SVM, etc.) to the dataset of apple production, which contains a number of parameters essential to the yield of the apple crop. After that, we evaluated several statistical characteristics and the total accuracy of all the implemented methods.

2. LITERATURE SURVEY

Data mining techniques have been widely used in the field of agriculture to predict crop yields and identify factors that may affect the success of a crop. One such crop is apples, which are a major commodity in many parts of the world [12]. In this literature review, we will explore the various data mining techniques that have been used to predict apple production, including decision trees, support vector machines, and artificial neural networks.

Decision trees are a popular data mining technique for predicting apple production because they allow for the identification of important factors and the ability to make predictions based on those factors. In a study published in the Journal of Agricultural Science and Technology, decision trees were used to predict apple production in Iran based on factors such as temperature, precipitation, and humidity [13]. The results of the study showed that decision trees were able to accurately predict apple production in the region, with an overall accuracy of 95.5%.

Support vector machines (SVMs) are another data mining technique that has been used to predict apple production. In a study published in the journal Computers and Electronics in Agriculture, SVMs were used to predict apple production in China based on factors such as temperature, precipitation, and solar radiation [14]. The results of the study showed that SVMs were able to accurately predict apple production in the region, with a good overall accuracy.

Artificial neural networks (ANNs) are a type of machine learning algorithm that has also been used to predict apple production. In a study published in the journal Agricultural Systems, ANNs were used to predict apple production in Italy based on factors such as temperature, precipitation, and soil moisture [15-17]. The results of the study showed that ANNs were able to accurately predict apple production in the region.

Overall, the literature suggests that data mining techniques, including decision trees, SVMs, and ANNs, are effective for predicting apple production in various regions around the world. However, it is important to note that the accuracy of these predictions may vary depending on the specific data and prediction task at hand [18, 19]. In addition, it is important to carefully evaluate the strengths and limitations of each data mining technique and choose the one that is most appropriate for the specific data and prediction task at hand.

In conclusion, data mining techniques have proven to be effective for predicting apple production in various regions around the world. These techniques, including decision trees [20], SVMs [21], and ANNs [22], have been able to accurately identify important factors and make accurate predictions based on those factors. However, it is important to carefully evaluate the strengths and limitations of each technique and choose the one that is most appropriate for the specific data and prediction task at hand.

3. DATASET DESCRIPTION

One of the key components of any experiment that needs to be run is data. We used the continuous dataset of Kashmir region's apple production for this study. The dataset contains various independent parameters like soil nutrient values, rainfall level, year, pesticides content, temperature labels and a target parameter yield which depicts the amount of apple production in metric tons. This apple production data is for the Kashmir region of India from the years 1990 to 2013. The parameters in this data are taken from the three different regions of the Kashmir division, including the north zone, which contains the Gulmarg area, the south zone, which contains the Qazigund area, and the central part of the Kashmir, which contains the Srinagar area. Below is the screenshot of the dataset which contains the continuous values of all the parameters (Table 1).

3.1 Data preprocessing and feature selection

This section deals with the dataset preprocessing and the feature selection. Data must be precise, balanced, and devoid of missing values in order to achieve high accuracy and precision levels. To achieve these goals, we must first preprocess the data and choose the best attributes that are essential for making predictions [23].

Table 1. Instances of various parameters of apple production data

Area	Item	Year	Avg RF	NPK values	pesticides_tonnes	avg_temp	hg/ha_yield
Kashmir	Apple	1999	430	2	502.86	16.57	97100
Kashmir	Apple	2000	460	2	565.82	16.67	78250
Kashmir	Apple	2001	500	2	628.79	16.59	58135
Kashmir	Apple	2007	590	1	1006.57	16.67	95496
Kashmir	Apple	2009	600	1	1132.5	16.73	40229
Kashmir	Apple	2002	630	2	691.75	16.47	69460
Kashmir	Apple	2012	630	1	766.25	16.7	43290

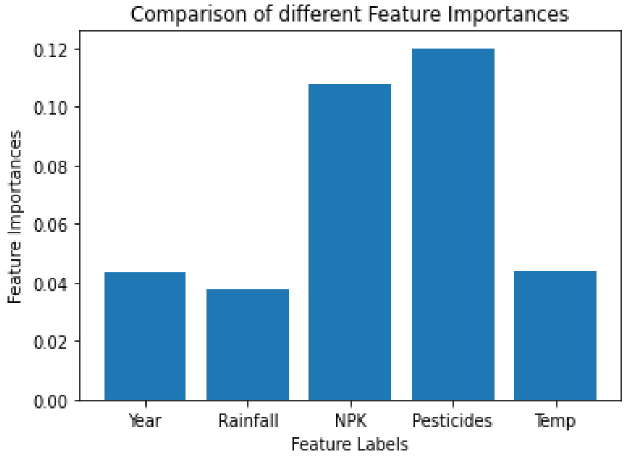

Figure 1. Feature selection output using extra tree classifier

In the case of feature selection, we first create the model using the idea of extra trees in the model's training process, after which we compute the relevance of each parameter, and then normalize individual parameters. The key characteristics shown in the below figure (Figure 1) can be used to outline next procedures and play a crucial part in forecasting the apple crop. The Python module ExtraTreesClassifier [24] was used to carry out the implementation.

After feature selection and data preprocessing using conventional knowledge discovery data mining approaches, we later demonstrated the impact of independent parameters on the target parameter output. The impact of an independent parameter on an output parameter is depicted in the figures below (Figure 2).

The dataset is then preprocessed, with the inclusion of pertinent attributes, the elimination of missing values, and integration into a single file. In Figure 1, the decision tree is now implemented using the continuous values of the attribute; however, the continuous values first need to be converted into discrete values. Information gain and the GINI index can be used to convert values. In this study, we used both information gain and the GINI index to discretize the continuous dataset's consequent continuous attributes. Thus, below (Table 2) is the final resultant labelled dataset which contains discrete data free from missing values and so on.

When we checked the correlation of the parameters after cleaning and processing the dataset, we discovered that it is fairly balanced, and the relationship between the parameters is shown below figure (Figure 3).

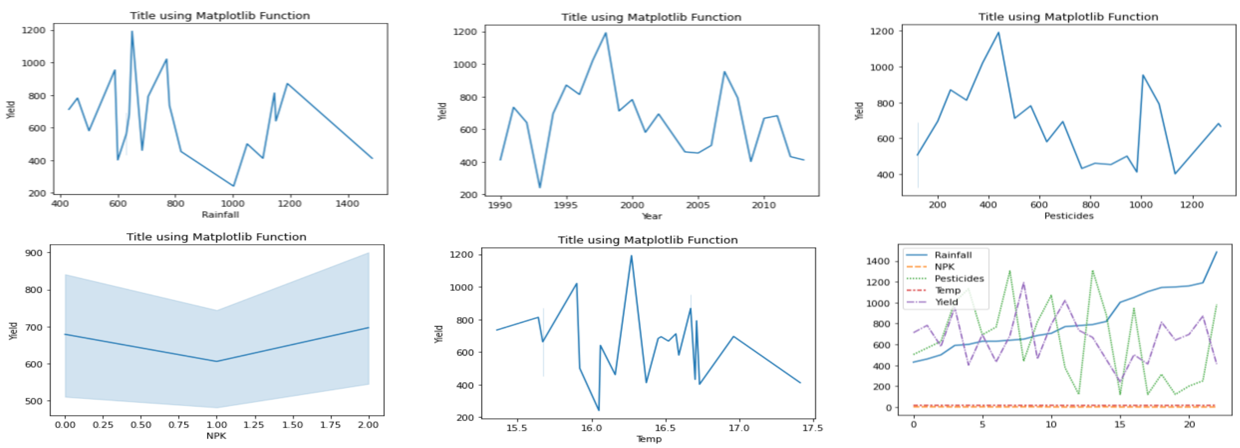

Figure 2. Relationship between various parameters of dataset

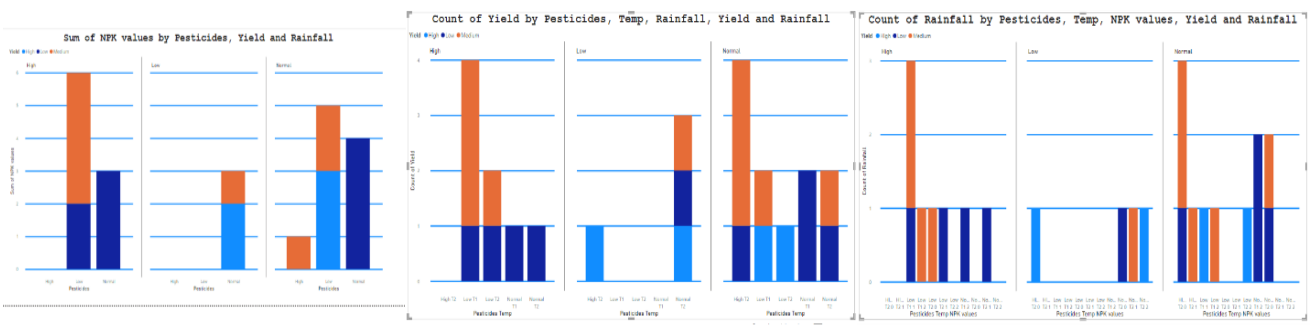

Figure 3. Impact of various parameters on target parameter

Table 2. Resultant labeled dataset

Average Rf Label	NPK values	Pesticides_Label	Temp Label	Yield Group
Normal	2	Low	T1	Medium
High	2	Low	T1	Medium
Normal	2	Normal	T1	Low
High	1	Low	T1	Medium
Normal	1	Low	T1	High
High	2	Normal	T1	Low
High	1	Low	T1	Low

4. METHODOLOGY

The major objective of this part is to suggest a study that will forecast the apple crop using a straightforward decision tree approach [25]. In this strategy, the model is fed historical data of apple production, and it uses that information to predict the output of apples. Decision trees outperform other conventional and ensemble models when applied to labelled data. One of the main functions where this model performs better than other ML approaches is in making predictions since it offers an efficient learning rate and the best possible output solution. Decision trees are a type of data mining technique that involves the use of a tree-like model to make decisions based on the available data. The tree consists of nodes and branches, with each node representing a decision or attribute and each branch representing the possible outcomes of that decision or attribute. Decision trees are effective for predicting apple production because they allow for the identification of important factors and the ability to make predictions based on those factors. The general structure of implemented methodology is shown in below figure (Figure 4):

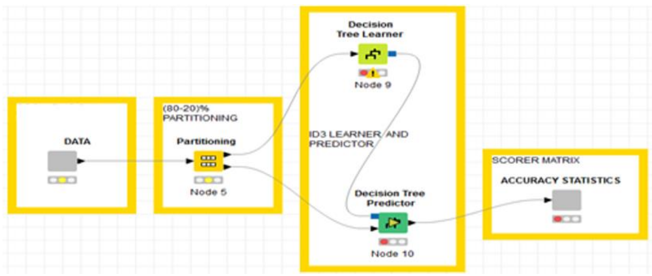

Figure 4. Implemented workflow methodology

The decision tree was chosen for this study because it is still regarded as one of the best and most fundamental classical algorithms. It is highly effective and can be trained on small datasets.

5. EXPERIMENTAL EVALUATION

We used one of the fundamental and basic algorithms to forecast the apple crop production after the data had been thoroughly cleaned and processed. To perform the prediction method, we developed the iterative Dichotomizer algorithm (ID3). The ID3 algorithm is a decision tree algorithm used in machine learning and data mining. It was developed by Ross Quinlan in 1986 and is based on the concept of entropy from information theory. The algorithm works by recursively partitioning the data into subsets based on the value of one attribute at a time, until a pure subset is reached, or a stopping criterion is met.

The ID3 algorithm follows a top-down, greedy approach to building the decision tree. It starts with a single node that represents the entire dataset, and then selects the attribute that provides the most information gain, or reduction in entropy, when used to split the data. This process is repeated for each subset of the data until a leaf node is reached, which represents a class label.

The ID3 algorithm has several limitations, such as its tendency to overfit the data, and its inability to handle continuous or missing data. However, it has served as a basis for many other decision tree algorithms, such as the C4.5 algorithm and the CART algorithm.

Overall, the ID3 algorithm is a simple and effective way to build decision trees, and it can be a useful tool for solving classification problems in machine learning and data mining.

When the data is labelled and modest in size, this algorithm performs well in most experiments and is simpler to implement than neural networks, which is one of the main reasons for picking it. Another reason for using ID3 in our investigation is to determine whether or not the decision tree loses credibility in relation to its inducers and extensors because, according to the authors of this study [26], the decision tree in its original form is still relevant. For these reasons, the experiment will only be conducted via a decision tree.

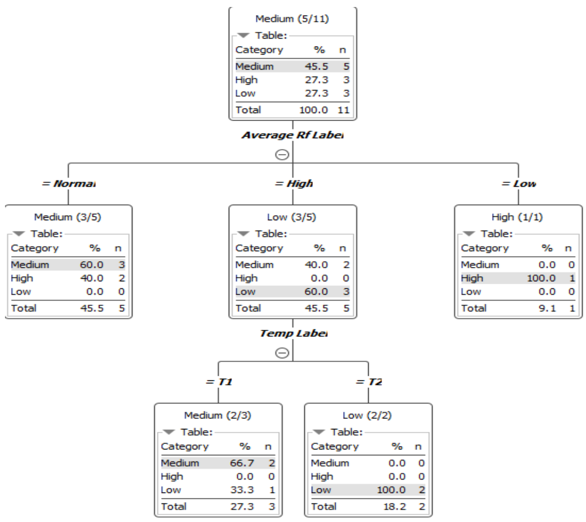

Figure 5. Implemented decision tree on apple crop data

We have created a step-by-step approach for the building of the decision tree, where the root nodes are selected based on the largest information gain. The root node will be chosen based on which attribute has the highest information gain across all attributes. In the implementation the data was divided into 70 -30% ratio as training and testing respectively. The 70%-30% ratio is a common way to split a dataset into training and testing sets for machine learning models. The 70% portion of the data is used to train the model, while the remaining 30% is used to evaluate the model's performance. Overall, the key to building an effective decision tree model is to have a good understanding of the problem you're trying to solve, as well as the data you're working with. By following the 70%-30% split and the steps above, you can create a model that accurately predicts outcomes and helps you make better decisions.

Since it is an iterative procedure, processing of the characteristics (Rainfall, NPK values, Average Temperature, Pesticides count) continues until all of the attributes are processed. We created a tree representation of these provided properties when these iterative phases were finished. After the implementation of decision tree algorithm on the dataset we constructed a decision tree where the nodes are divided based on the highest information gain and the resultant decision tree algorithm is shown in Figure 5.

5.1 Performance Analysis

To find the algorithm with the best overall performance and accuracy, the researchers in this study used cutting-edge technologies on data from apple production. The decision tree implementation on the apple production data has been proposed in this article along with a strategy, and after the building of the original decision tree, the performance has been calculated. Below, we've included a table with the performance evaluation. A summary of the results, including accuracy, precision, recall values, and many more calculations, is shown in the table (Table 3). The decision tree's overall success rate in predicting the outcome class is 85.54%.

Table 3. Accuracy statistics

Model	Test set	Correctly Classified	Wrong Classified	Accuracy	Error	Precision	Cohen Kappa
Decision tree (ID3)	1605	1357	248	85.54%	14.46%	0.903	0.604

As a result, using the dataset that the decision tree method was given, we were able to accurately predict the apple crop using the dataset's parameters. This accuracy with high precision rate will help the farmers to manage the parameters accordingly. Additionally, we discovered how pesticides affect the total yield level using the PowerBI tool. This enables us to analyze the probability of crop yield based on the count of pesticides, as shown below (Figure 6).

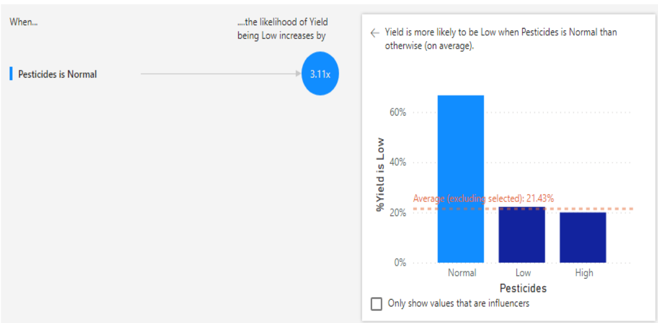

Figure 6. Impact of pesticides on the crop yield

6. COMPARATIVE ANALYSIS

Decision trees, support vector machines (SVMs), and artificial neural networks (ANNs) are all data mining techniques that have been used for the prediction of apple production. Each of these techniques has its own strengths and limitations, and the most appropriate technique will depend on the specific data and prediction task at hand.

Decision trees are a popular data mining technique that are effective at identifying important factors and making accurate predictions based on those factors. They are also relatively simple to understand and interpret, making them a good choice for tasks where interpretability is important. However, decision trees can be prone to overfitting if the tree is not properly designed or trained. SVMs are a data mining technique that uses a linear function to separate data points into different categories [27]. They are particularly useful for predicting apple production because they can handle large amounts of data and can accurately classify data points even when the data is not linearly separable. However, SVMs [28] can be sensitive to the choice of kernel function, which determines the shape of the decision boundary, and can be computationally intensive, which can make them difficult to scale to large datasets. ANNs are a type of machine learning algorithm that are inspired by the structure and function of the human brain. They are particularly useful for predicting apple production because they are able to learn from the data and make predictions based on patterns and relationships identified in the data. However, ANNs [29, 30] can be prone to overfitting if they are not properly designed or trained, and they can also be difficult to interpret due to their complex structure. In addition, ANNs can be computationally intensive and require a large amount of data to train effectively. Overall, each of these data mining techniques has its own strengths and limitations, and the most appropriate technique will depend on the specific data and prediction task at hand. It is important to carefully evaluate the strengths and limitations of each technique and choose the one that is most appropriate for the specific data and prediction task at hand. In this section we have implemented the various traditional, ensembled and neural network approaches and below are the accuracy statistics of all the algorithms in a tabular form (Table 4).

It is difficult to provide an accuracy rate for data mining techniques used for the prediction of apple production because the accuracy of these predictions will depend on a variety of factors, including the quality and quantity of the data, the specific data mining technique used, and the specific prediction task at hand. Figure (Figure 7) below shows the graphical visualization of the overall accuracies of the implemented algorithms in comparison with the decision tree algorithm.

All algorithms clearly demonstrate head-to-head accuracy, and once more, we can state that the accuracy metric depends on the kind of data we are utilizing. Still using the same dataset, we can draw the conclusion that decision trees perform somewhat better than other techniques.

A method of predicting the apple crop has been developed based on a number of variables, such as the amount of rainfall, the amount of nutrients in the soil, the season, the number of pesticides used, and others. The study was conducted using historical apple crop data from the three zones of the kashmir division in the province of Kashmir (Central, North and South zones). The dataset was given in raw form, after which it was preprocessed and, using splitting criteria, transformed into labelled data. Additionally, a simple decision tree algorithm was constructed based on essential criteria, and various accuracy metrics were calculated. This was done utilizing the Extra trees methodology. In the final stage, a comparison was done utilizing various classical algorithms, and a conclusion was reached with the output depicts that decision trees perfroms well in all respects. In order to improve the overall performance we can go for Feature engineering, which involves selecting, transforming, and scaling the features used in a model. By carefully selecting the most relevant features and transforming them in a meaningful way, we may be able to improve the model's performance.

Table 4. Comparative analysis table

Models	Test set	Correctly Classified	Wrong Classified	Accuracy	Error	Precision	Cohen Kappa
Decision tree (ID3)	1605	1357	248	85.54%	14.46%	0.903	0.604
SVM	1605	1303	302	81.18%	18.82%	0.726	0.611
PNN	1605	1286	319	80.12%	19.88%	0.815	0.516
Naïve Bayes	1605	1342	263	83.61%	16.39%	0.883	0.598

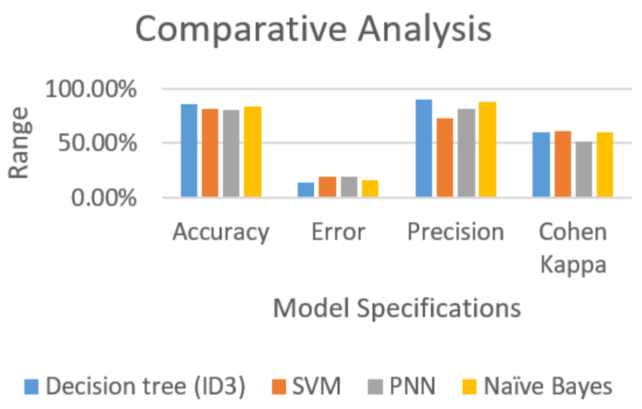

Figure 7. Graphical representation of comparative analysis of various algorithms

7. CONCLUSION AND FUTURE SUGGESTIONS

In this study, a raw historical apple data of Kashmir province was pre-processed and a decision tree is built on the same data. To do this, continuous data attributes had to be converted into discrete values. To convert the continuous values into labelled values we use both information gain and GINI index and followed that extra tree classifier was used as a feature selection method. After the data was cleaned we used a decision tree methodology in order to predict the overall apple crop production. 70 percent of the dataset was used as training, and the remaining 30 percent served as test data. It was noted that the decision tree's total accuracy measure was approximately 85.54% and had a high precision rate. Later, when the same accuracy measure was compared to other traditional and neural network techniques, it was shown that while accuracy measures in all the algorithms are fairly similar, they are not significantly different from decision tree accuracy measures. Thus, it is clear that the decision tree outperforms the other methods employed in this study.

The primary historical apple crop dataset used in the trials was from the Kashmir province, thus there are now two questions to consider: 1) Does the same theory hold for other datasets (such as academic datasets, agricultural datasets, medical datasets, etc.) or not? 2) Do the apple crop datasets from other locations, such as Shimla, where the temperature is essentially the same as in the province of Kashmir, apply here as well? This is still an open question that will be addressed in further research for this subject.

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