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Flood Prediction System using Multilayer Perceptron Classifier and Neural Networks

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Abstract - *Floods are one of the most catastrophic natural disasters, and, due to their complex nature, it is not easy to create a predictive model. The advanced research works on flood prediction models have contributed to risk reduction, policy suggestion, minimization of the loss of human life, and reduced property damage associated with floods. In general, neural networks are used in the development of prediction systems, to mimic the complex mathematical expressions of the physical processes of floods providing better performance and cost-effective solutions. The best algorithm for prediction of flood occurrence is analyzed by comparing MLP with Logistic Regression, Support Vector Machine, K Nearest Neighbor algorithm and accuracy values are calculated with an evaluation of classification report and by precisely examining the confusion matrix parameters. The proposed system analyses the dataset using Multilayer Perceptron Classifier (MLP) algorithm to train the predictive model, and with a developed graphical user interface, real time flash flood predictions are made.*

Key Words: Deep Learning, Neural Networks, Multilayer Perceptron, Classification, Floods, Rainfall.

1. INTRODUCTION

Floods are amongst the most catastrophic natural disasters, causing massive damage to human life, infrastructure, agriculture, and the socioeconomic system. Governments are under enormous pressure to develop reliable and accurate maps of flood risk areas and further plans for sustainable flood risk management, focusing on prevention, protection, and preparedness. Many flood control measures are being implemented to reduce the losses incurred because of it. But these flood control measures have not been that effective in areas that are prone to flash floods. Due to its capability to predict future events, machine learning has contributed a lot in preventing many natural disasters like floods, earthquakes.

Being an Artificial Intelligence application, Machine Learning is where the systems can learn from past data, identify patterns, and learn to make predictions with minimal human interaction. It provides computers with the ability to learn and make decisions without being programmed explicitly. It mainly focuses on developing computer programs that can change when exposed to new data. The process of training and testing of a machine learning model involves the use of various specialized machine learning algorithms. The methodology follows the process of feeding the training data to an algorithm, and the algorithm uses this training data to give predictions on new test data. Machine learning can be roughly classified into three categories.[2] They are Supervised Learning, Unsupervised Learning, and Reinforcement Learning. In Supervised learning, the prediction model is given a training dataset with both the input data and the corresponding output data. In Unsupervised Learning, the training set has no labels, and the algorithm tries to find a structure or a pattern in the given unlabelled data set. The algorithms used for unsupervised learning are of two types called clustering algorithm and the expectation-maximization algorithm. In the case of reinforcement learning, the algorithm dynamically interacts with its environment, and it receives positive or negative feedback to improve its performance.

Data scientists use many different kinds of machine learning algorithms to discover patterns that lead to actionable insights. At a high level, these different algorithms are classified as supervised and unsupervised learning algorithms based on their way of training and the type of dataset they use to make predictions. Supervised learning can be further grouped into Classification and Regression problems. Both problems have a goal: constructing a succinct prediction model that predicts the value of the dependent attribute from the input attribute variables. The difference between the two problems is that the dependent attribute is numerical for regression and categorical for classification. Classification [3] is a supervised learning approach that involves the process of predicting the label or classes of given data points. The task of predictive classification modelling is an approximation of a mapping function from input variables(X) to discrete output variables(Y). This data set may be bi-class or multi-class containing discrete output values. Some well-known examples of classification problems could be document classification and speech recognition. In a regression problem, the results are predicted within a continuous output where the input variables are mapped to some continuous function. Regression problems are categorized into various types, such as Simple Linear Regression, Polynomial Regression, Random Forest Regression, Decision Tree Regression, Support Vector Regression.

Unsupervised learning mainly deals with unlabelled data, and using the clustering algorithm; it finds structures or patterns in the given dataset. It allows you to perform more complex processing tasks compared to supervised learning. Unsupervised learning can be classified into Parametric unsupervised learning and Non-parametric unsupervised learning. The parametric unsupervised learning algorithm makes use of the Expectation-maximisation algorithm to construct Gaussian Mixture Models to predict the class of the given unlabelled data. In Non-parametric unsupervised learning, the data is grouped into clusters by finding a pattern or a structure in a collection of unlabelled data. The clustering problem is considered as the most desirable unsupervised learning problem. Clustering algorithms can be classified as Exclusive Clustering, Overlapping Clustering, Hierarchical Clustering, and Probabilistic Clustering.

The goal of this system is to develop a machine learning model for real-time flood forecasting, to potentially replace the updatable multi-layer perceptron (MLP) neural network [4] models by predicting results in the form of accuracy. In recent times, sub-pass or low-lying areas in cities are most vulnerable to waterlogging. In these flood-prone locations, water gets accumulated in a short period. Relative elevation, surface runoff, and insufficient passage of water to drainage are critical points in the development of waterlogging. Thus, flash flood forecasting at these places is essential. This project's scope is to train a prediction model with the dataset of rainfall records of all the states in India to predict flood warning prior. This is to reduce the inefficiency in predicting the flood [5] and to improve the accuracy analysis in predicting floods prior, which would, in turn, save lives and also to save lots of meteorological efforts and assets in predicting flood occurrence.

2. EXISTING SYSTEM

The conventional strategies of flood forecasting are expensive and highly complicated. Weather and rainfall forecasting is a significant task behind the prediction [1] of a flood. Weather forecasting involves simulations based on physics and differential equations. The rainfall forecast is done using radars and satellite imaging. A Doppler weather radar is used to locate the precipitation and detect the motion of rain droplets. Dedicated weather satellites provide images using which information about rainfall can be deduced. In short-term flash flood prediction in urban areas, a theoretical model incorporating the factors influencing flood is established using the power of machine learning techniques, which is used to estimate floods ahead of time. Rapid urbanization, climate change, and extreme rainfall have resulted in a growing number of cases of urban flash floods in recent times. It is crucial to predict the occurrence of a flood so that its aftermath can be minimized.

As the name suggests, an urban flash flood occurs in an urban area in a short period. Hence, to reduce its impact, short-term forecasting is used for prediction of the very near future incident. In orthodox methods of flood forecasting, current weather conditions are examined using conventional methods such as radar, satellite imaging, and calculations involving complicated mathematical equations. The recent developments in Machine Learning (ML) and Information and Communication Technology (ICT) has helped us to study this hydrological problem from a different perspective. The aim is to design a theoretical model considering the parameters causing the urban flash flood and predict the event. The drawbacks of this system include the following,

- To implement a model for an urban area in which short-term forecasting of a flood is a complex scenario, including multiple factors, is imagined where a possible real-world scenario is undertaken.
- It can't thereby determine the regularity of rainfall data and achieve more accurate prediction results of a flash flood.

3. PROPOSED SYSTEM

Flood is one of the catastrophic natural disasters which has resulted in the loss of many human lives, and other damages. Different types of floods like river flood, urban flood, coastal flood, and flash flood have been observed over the years. A flash flood occurs as a result of highly intense rainfall in a short time. This kind of flood is seen typically in urban areas where the underlying ground cannot cope, or drain excess water away via the sewage system and drainage canals quickly, which can be evidenced by the destructive impact of floods in cities such as Mumbai, Chennai, and in states like Telangana and Kerala. Poor urban planning, inaccurate and delayed forecasting, and inadequate flood mitigation systems are the main reasons behind it. This system aims to collect data from all the states of India and form a generalized dataset. A machine learning algorithm is applied to the labelled dataset, and patterns are extracted, which, in turn, obtain maximum accuracy with real-time input.[8] In general, the dataset collected for predicting is split into a Training set and Test set. Generally, 7:3 ratios are applied to split the Training set and Test set. The Data Model is then created using a Multi-Layer Perceptron Classifier, and the resulting data set is then passed through it for prediction.

Flood prediction models are of significant importance for hazard assessment and extreme event management. Robust and accurate prediction [7] contributes highly to water resource management strategies, policy suggestions and analysis, and further evacuation modelling. Thus, the necessity of advanced systems for short-term and long-term prediction of flood and other

hydrological events is strongly emphasized to alleviate the damage. However, the prediction of a flood, time, and occurrence location is fundamentally complex due to the dynamic nature of climatic conditions. The vast majority of Artificial Neural Network models for flood prediction are often trained with a Back Propagation Neural Network. The Multilayer Perceptron is a class of Feed Forward Neural Network that utilizes the supervised learning of Back Propagation for training the network of multi-layered interconnected nodes, which has recently gained popularity. The models designed using MLP were found to be more efficient, with a better generalization ability, in an assessment of Artificial Neural Network classes used in flood modelling. The advantages of the proposed system are listed below,

- These reports investigate the applicability of machine learning techniques for air quality forecasting in operational conditions.
- It highlights some observations on future research issues, challenges, and needs.
- As Machine Learning is a field of artificial intelligence, it helps in inducing regularities and patterns, providing a straightforward and less complicated implementation with less computation cost and high performance compared to physical models.

3.1 Overview of the System

The evaluation of the prediction accuracy of the classifiers is carried out using data validation, and the results have been compared to obtain accuracy. It has to find the accuracy of the training dataset, accuracy of the testing dataset, specification, false-positive rate, precision, and recall by comparing algorithms using python code. The following Involvement steps are,

- Define a problem
- Preparing data
- Evaluating algorithms
- Improving results
- Predicting results

The steps involved in Building the data model are depicted below.

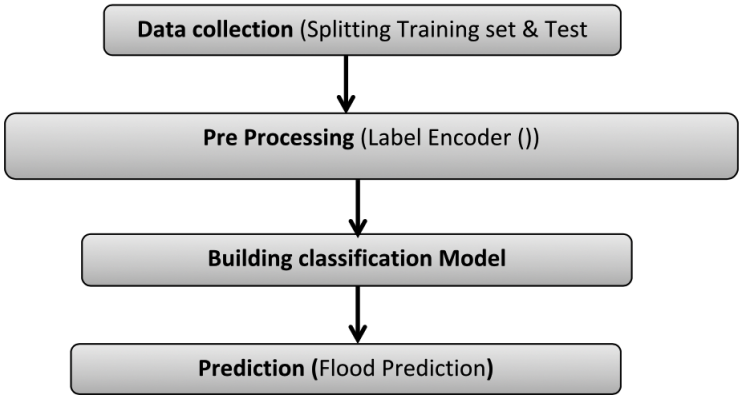


Fig-1: Process Flow Diagram

3.2 Multilayer Perceptron

A multilayer perceptron can be defined as a class of feedforward artificial neural networks (ANNs). Multilayer perceptrons are sometimes referred to as neural networks, especially when they have a single hidden layer. A Multi-Layer Perceptron or Multi-Layer Neural Network contains one or more hidden layers (apart from one input and one output layer). While a single layer perceptron can only learn linear functions, a multilayer perceptron can also learn non – linear functions. An MLP consists of at least three significant layers, an input layer, a hidden layer, and an output layer. Except for the input nodes, each node in the network is a neuron that makes use of a non-linear activation function. MLP utilizes a supervised learning technique called backpropagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable [12].

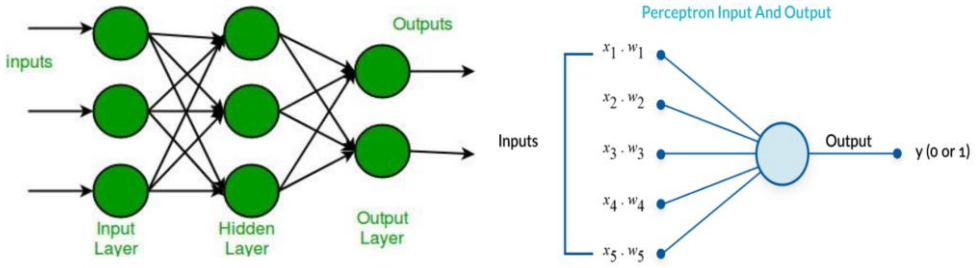


Fig-2: Multilayer Perceptron

3.3 System Architecture

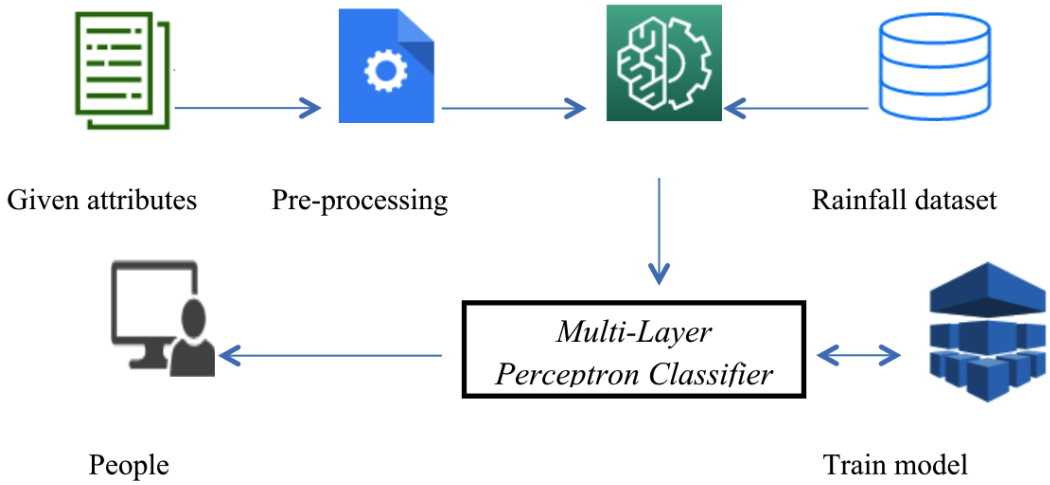


Fig-3: Architecture of the Proposed System

Modules:

- Data validation and pre-processing technique (Module-01)
- Create a predicted variable by rainfall range (Module-02)
- Performance measurements of ML algorithms (Module-03)
- Performance measurements of MLP classifier neural network (Module-04)
- GUI based prediction of the flood by rainfall (Module-05)

Variable Identification Process / Data Validation Process:

The error rate of the Machine Learning (ML) model can be identified using specific validation techniques, which can be considered as close to the true error rate of the dataset. If the volume of the data is large enough to be representative of the population, we may not have a need for the validation techniques. However, in real-world scenarios, to work with samples of data that may not be a true representative of the population of a given dataset. To find the missing value, duplicate value and description of data type, whether it is float variable or integer, are mentioned. The sample of data is used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyperparameters. The evaluation becomes more biased as a skill on the validation dataset is incorporated into the model configuration. The designed model is evaluated frequently using a validation set. Data identification helps us to understand the data and its properties which will help us to choose which algorithm shall be used to build the prediction model. For example, time-series data can be analyzed by regression algorithms; classification algorithms can be used to analyze discrete data.

Variable identification with Uni-variate, Bi-variate, and Multivariate analysis:

- Import libraries for access and functional purpose and read the given dataset
- General Properties of Analyzing the given dataset

- Display the given dataset in the form of a data frame
- Show columns
- The shape of the data frame
- To describe the data frame.
- Checking data type and information about dataset
- Checking for duplicate data
- Checking Missing values of the data frame
- Checking unique values of the data frame
- Checking the count values of the data frame
- Rename and drop the given data frame
- To specify the type of values.
- To create extra columns.

Data Validation/ Cleaning/Preparing Process:

This process involves variable identification by data shape, data type, and evaluating the missing values, duplicate values. The process of data cleaning varies from dataset to dataset. The primary goal of data cleaning is to detect and remove errors and anomalies to increase the value of data in analytics and decision making. A sample of data, known as the validation dataset, is held back from training the model, that can be used to make the best use of validation and test datasets when evaluating your models, giving an estimate of model skill while tuning models and procedures.

Data Pre-processing:

Pre-processing is the process where the data is transformed prior to feeding it to the algorithm. This is done in order to convert the raw data into a clean dataset for better results after feeding it to the algorithm. As the data gathered are from different sources, and not uniform, it is not feasible for analysis. To achieve better results from the applied model in the Machine Learning method of the data has to be in a proper manner. Some specified Machine Learning models need information in a specified format; for example, the Random Forest algorithm does not support null values. Therefore, to execute random forest algorithms, null values have to be managed from the original raw data set.

Exploration Data Analysis of Visualization:

Data Visualization is considered as a very important skill in applied statistics which focus on quantitative descriptions and estimations of data, and machine learning. Data visualisation provides an important suite of tools for gaining a qualitative understanding which can be useful when exploring and getting to know a dataset which can help with identifying patterns, corrupt data, outliers and much more. Data visualization can also be used to demonstrate key relationships in plots and charts that are more visceral.

Outlier Detection Process:

Many machine learning algorithms are known to be sensitive to range and distribution of attribute values in the input data. Outliers in those data can mislead and skew the training process of the algorithms which will result in longer training times, less accurate models and ultimately poorer results. Even before the process of training the model, the outliers can result in misleading representations hence resulting in misleading interpretations of collected data. Outliers are capable of skewing the summary distribution of attribute values in statistics like mean, standard deviation and in plots such as scatter plots, histograms, compressing the body of the data.

Outliers are also capable of representing examples of data instances which are relevant to the problem such as anomalies in the case of fraud detection and computer security. It couldn't fit the model on the training data, and this can affect the model to work inaccurately in case of real data. Hence, we must ensure that our model gets the correct patterns from the data, and not receiving too much noise. Cross Validation is a process where we train our model using the subset of the dataset and then evaluating using the complementary subset of the dataset. Cross validation is advantageous as it provides a more accurate estimate of out of sample accuracy and also for its more efficient use of data as every observation is used for both training and testing.

The steps of cross-validation are as follows:

1. Some portion of a sample dataset is reserved.
2. Train the model using the rest dataset.

3. Test the trained model using the reserved portion of the dataset.

4. ALGORITHMS AND TECHNIQUES

4.1 Algorithms

Logistic Regression:

Logistic Regression is a machine learning algorithm that predicts the probability of a categorical dependent variable. It is a statistical way of analyzing a set of data that comprises more than one independent variable that determines the outcome. The outcome is then measured with a dichotomous variable. The goal of this algorithm is to find the best model to describe the relationship between a dichotomous characteristic of interest and a set of independent variables. In this algorithm, the dependent variable is a binary variable that contains data coded as 1 or 0. In other words, the logistic regression model predicts P(Y=1) as a function of X.

Support Vector Machines:

SVM uses a classifier that categorizes the data set by setting an optimal hyperplane between data. This classifier is chosen as it is incredibly versatile in the number of different kernel functions that can be applied, and this model can yield a high predictability rate. Support Vector Machine is one of the most popular and widely used clustering algorithms. It belongs to a group of generalized linear classifiers and is considered as an extension of the perceptron. It was developed in the 1990s and continues to be the desired method for a high-performance algorithm with a little tuning.

K-Nearest Neighbor (KNN):

K-Nearest Neighbor is one of the supervised machine learning algorithms that stores all instances corresponding to training data points in an n-dimensional space. For real-valued data, the algorithm returns the mean of k nearest neighbors, and in case of receiving unknown discrete data, it analyses the closest k number of instances which is saved and returns the most common class as the result of the prediction. In the distance-weighted nearest neighbor algorithm, the contribution of each of the k neighbors is weighed according to their distance, giving higher weight to the closest neighbors. The K-Nearest Neighbor algorithm is a classification algorithm and is robust to noisy data as it averages the k-nearest neighbors. The algorithm first takes a bunch of labeled points and analyses them to learn how to label the other points. Hence, to label a new point, it looks at the closest labeled points to that new point and has those neighbors vote, so whichever label the most of the neighbors have is the label for the new point. This algorithm makes predictions about the validation set using the entire training set. Only by searching through the entire training set to find the closest instances, the new instance is predicted. Closeness is a value that is determined using a proximity measurement across all the features involved.

4.2 Performance Analysis Metrics

True Positive: It is an outcome where the model correctly predicts the positive class. The outcome is considered as true positive when the system can correctly predict that an incident has indeed occurred.

True Negative: It is an outcome where the model correctly predicts the negative class. The outcome is considered as true negative when the system can correctly predict that the particular incident has not occurred.

False Positive: False Positive is an accuracy measure where the model mispredicts the positive class. The outcome is considered as False Positive when the system cannot correctly predict that the particular incident has occurred.

False Negative: False Negative is an accuracy value where the model mispredicts the negative class. The outcome is considered as False Negative when the system cannot correctly predict that the particular incident has not occurred.

Sensitivity: Sensitivity is a measure of the proportion of true positive values, that is, the actual number of positive cases that are correctly predicted as positive. It is also known as Recall value. There exists another proportion of actual positive cases that are mispredicted, which can be represented in the form of a false negative rate. Therefore, the sum of sensitivity and false-negative rate value is 1.

Mathematically, sensitivity can be calculated as the following:

Sensitivity/Recall = (True Positive) / (True Positive + False Negative)

The higher value of sensitivity would mean a higher value of the true positive and lower value of false negative. The lower value of sensitivity would mean a lower value of the true positive and higher value of false negative.

Specificity: Specificity is defined as the measure of the proportion of true negative, which is the actual number of negative cases that are predicted as negative. Simultaneously, another proportion of actual negative values, which got predicted as positive, is termed as a false positive rate. The sum of specificity and false positive rate value will always be 1.

Mathematically, specificity can be calculated as the following:

Specificity = (True Negative) / (True Negative + False Positive)

The higher value of specificity would mean a higher value of true negative and lower false-positive rate. The lower value of specificity would mean a lower value of the true negative and higher value of false positive.

Precision: The proportion of positive predictions that are actually correct.

Precision = TP / (TP + FP)

Precision is calculated by dividing the number of correctly predicted positive observations by the total number of predicted positive observations. High precision relates to the low false-positive rate.

Recall: The proportion of positive observed values correctly predicted. (The proportion of actual defaulters that the model correctly predicts)

Recall = TP / (TP + FN)

Recall (Sensitivity) - Recall is calculated by dividing the number of correctly predicted observations to the total number of observations in an actual class.

F1 Score: F1 Score is defined as the weighted average of Precision and Recall values. Hence both false negative and false positives values are taken into account. When there's an uneven class distribution, the F1 Score value is generally more useful when compared to Accuracy value. On the other hand, Accuracy value worksheets best when the values of false positive and false negatives have a similar cost. If both values are different, then Precision and Recall values are taken into account.

General Formula:
F- Measure = 2TP / (2TP + FP + FN)

F1-Score Formula:
F1 Score = 2*(Recall * Precision) / (Recall + Precision)

6. RESULTS AND DISCUSSION

Table-1: Comparison of Accuracy Results

	Precision	Recall	F1-Score	Sensitivity	Specificity	Accuracy (%)
Logistic Regression	0.99	0.96	0.98	0.96	0.75	95.33
Support Vector Machine	0.96	1	0.98	1	0	95.85

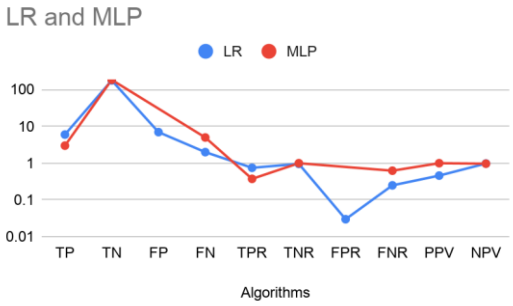
K-Nearest Neighbours	0.97	0.98	0.98	0.98	0.37	95.85
Multilayer Perceptron	0.97	1	0.99	1	0.37	97.4

Table 1 compares the Accuracy results of the Logistic Regression, Support Vector Machine, K-Nearest Neighbour, and Multilayer perceptron algorithms. From the calculated values, we can observe that the Support Vector Machine and Multilayer Perceptron has comparatively better results. And from further comparison, we can conclude that Multilayer Perceptron gives the highest accuracy percentage value.

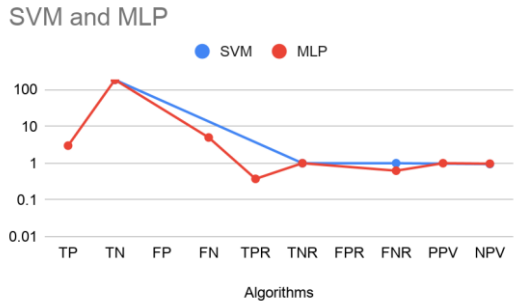
Table-2: Comparison of Confusion Matrix Parameters

Algorithms	TP	TN	FP	FN	TPR	TNR	FPR	FNR	PPV	NPV
LR	6	178	7	2	0.75	0.96	0.03	0.25	0.46	0.98
SVC	0	185	0	0	0	1	0	1	-	0.95
KNN	3	182	3	5	0.37	0.98	0.01	0.62	0.5	0.97
MLP	3	185	0	5	0.375	1	0	0.625	1	0.97

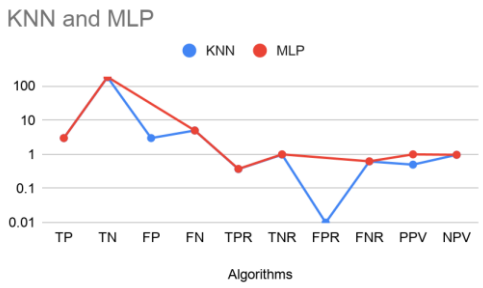
Table 2 compares the True Positive, True Negative, False Positive, False Negative, True Positive Rate, True Negative Rate, False Positive Rate, False Negative Rate values of Logistic Regression, Support Vector Machine, K nearest Neighbour and Multilayer Perceptron algorithms. From the calculated values, we can conclude that Multilayer Perceptron has produced the best results. This can be further carefully investigated using the below graphs.



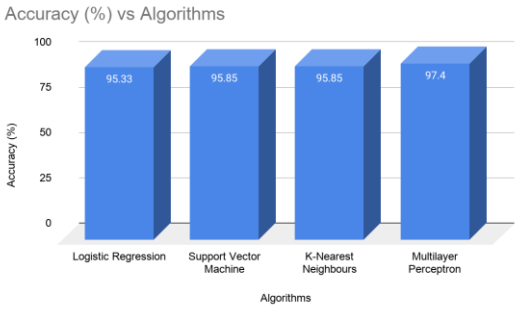
a) Logistic Regression vs MLP



b) SVM vs MLP



c) KNN vs MLP



d) Comparison of accuracy of LR, SVM, KNN and MLP

Chart-1: Performance and Accuracy Comparison Graph

The graph (a) compares the comparison matrix parameter values between Multilayer Perceptron and Logistic Regression algorithms. It can be observed that the accuracy values of Multilayer Perceptron are comparatively more efficient when

compared to Logistic Regression. The graphs (b) and (c) compare the matrix parameter values between the Multilayer Perceptron and Support Vector Machine and K nearest Neighbour and Multilayer Perceptron algorithms, respectively. From the two graphs, we can conclude that Multilayer Perceptron algorithms have efficient performance compared to K nearest Neighbour and Support Vector Machine Algorithms. This statement can be further supported by the graph in Figure 5, which compares the accuracy percentage of all the four algorithms with Multilayer perceptron algorithms having the highest percentage of 97.4%.

TESTING RESULTS:

Input: Output:

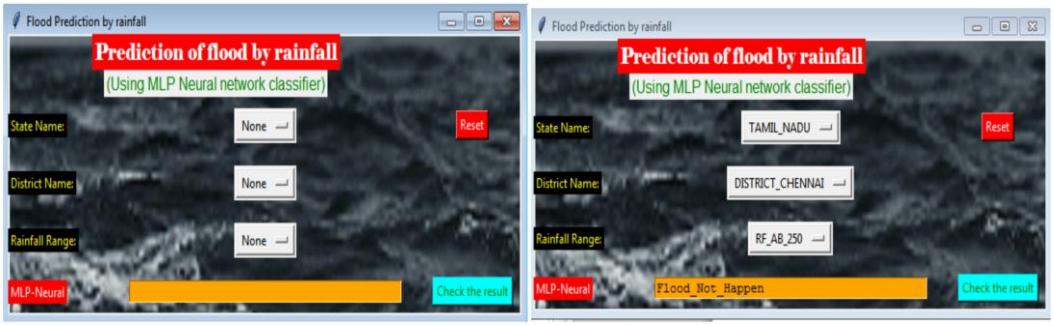


Fig-4: Screenshots of the Result

7. CONCLUSION

The analytical process started with data cleaning and processing, finding missing value, exploratory analysis, and finally, model building and evaluation. Finally, we predict the flash flood using machine learning algorithms, which gave different results. From the above observations and analysis, the best algorithm for flood prediction is the MLP algorithm (97.40%).

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