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Title **EFFECTIVE MACHINE LEARNING ALGORITHM FOR HIGH ACCURACY TOWARDS EARTHQUAKE IMPACT ANALYSIS**

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EFFECTIVE MACHINE LEARNING ALGORITHM FOR HIGH ACCURACY TOWARDS EARTHQUAKE IMPACT ANALYSIS

KIRAN KUMAR POLU , P. SREENIVASULU

ABSTRACT

Mega structures either man made or naturally formed may be affected in a devastative way by natural disasters among which an earth quake is one such natural disaster. Based on vibrations caused by seismic waves which flow during crust of the earth, measurement of earth quake can be done through seismometers. Damage grades are used to determine earth quake damage. Such damage grades range from one to five.

To estimate the damage grade of a structure, a formerly gathered data set which contains a valid set of parameters can be used. Existing machine learning classifier and clustering algorithms are available in predicting the grade of damage for a particular mega structure. A unique identification string will be assigned to the damage grade that is to be predicted.

Evaluation is done for a set of attributes using various machine learning algorithms like NaïveBayes, RandomForest, K-NN and XGBoost to consider the best fitting algorithm. Each given algorithm will perform a clear and thorough analysis on predicted attribute and analysis of data which supports earth quake impact mitigation. Best fitted algorithm can be determined by using accuracy graph.

Keywords—Classifier algorithms, Naive Bayes, Random Forest, K-Nearest Neighbors, XGBoost, predictive analysis, Machine Learning, tree pruning, hyper parameters tuning.

INTRODUCTION

An earthquake is a devastating event that can cause harm to people and their belongings as well as have un-favourable effects on the natural world. Earthquakes have historically caused unfathomable destruction of megastructures and assets, leading to the deaths of countless individuals around the globe. Numerous domestic and international groups implement a wide range of earthquake early warning and safety protocols to lessen the damage caused by such events. Predicting the extent of earthquake damage to buildings using machine learning is a realistic possibility. It may be used to determine which structures are safe and which are not, which improves the effectiveness of rescue operations and helps people survive the aftershock of an earthquake.

This is done by assigning each structure a damage grade based on criteria such as the type of material it was built with, how old it is, the quality of its foundation, and the number of stories it has. Counting the number of households and potential casualties in each section of a district is important. This allows relief forces to be distributed ward-wise proportionally and prioritised based on damage assessment. This type of model can be an effective and economical way to save lives quickly. The number of lives lost and the amount of property damage can be used to determine how to best distribute resources like food, clothing, medical care, and money..

LITERATURE SURVEY

[1] Y. Wan-Jun, W. Jian and Z. Huai-Lin, "Research on Risk Management of Gas Safety based on Big Data," 2018. [7]

Big data theory proposes a safety management analysis tool to improve coal mine gas safety management. First, gas threats are classified using behavioural safety theory. Use HDFS to store hazardous behaviour and unsafe physical state detected by behaviour observers, then use the MapReduce-based parallel FP-growth algorithm to find recurrent and dangerous unsafe behaviours in everyday operations, and construct a Hadoop-based gas behaviour security management model. Experimental results suggest that the model is useful for implementing gas safety management in coal mines. Through risky behaviour and physical state, organisations can find safety management flaws and enhance their system. It could improve coal mine safety and reduce gas mishaps..

[2] Long Wang, Xiaoqing Wang, Aixia Dou, Dongliang Wang "Study on construction seismic damage loss assessment using RS and GIS" 2014. [8]

In this study, we present a rapid evaluation procedure suitable for use in cases of earthquake emergency. One version of the system is based on a damage index, while the other uses image classification to extract damage information from remote sensing photos. The damage index mode is based only on good old-fashioned eyeball testing. Following the provision of an expert-provided damage index, ground intensity data can be retrieved, and loss estimate parameters can be obtained using an experienced vulnerability matrix. Images can be sorted into categories using a digital image processing technology. The categorization result, which lists buildings in ascending order by type and ascending order by damage degree, can be used to derive these loss estimate parameters. In addition to introducing the models used for assessments, this section explains how to extract relevant parameters from a wide range of data sources by analysing the action of multi-resourced estimate data.

[3] Industrial Safety and Accident Prevention; A Managerial Approach Industrial Safety and Accident Prevention 2013 [9]

To gain an edge in the marketplace, businesses are reorienting their production processes. Finding the source of the production system's issues is crucial for fixing them. This article examines a section of firms' production systems in order to identify issues with the safety system, propose solutions, and offer suggestions for how those systems might better help businesses reach their objectives and prevent accidents. The rising incidence of workplace accidents has prompted us to focus on improving factory safety.

[4] PaiviHamalainen, JukkaTakala, KaijaLeenaSaarela, "Global estimates of occupational accidents", vol. 1,pp. 2-3, 2005 [10]

This study analyses global and country workplace injuries and diseases. Methods: ILO, WHO, EU, ASEAN, and national institutions provided sources. When missing, proxy countries were utilised. Results: We believe 2,3 million deaths each year are work-related. Work-related illnesses cause 2 million deaths, while occupational injuries cause the rest. Cardiovascular diseases and cancer were the leading work-related ailments globally, followed by industrial injuries and infectious disorders.

[5] H Takata, H. Nakamura, T Hachino "On prediction of electric power damage by typhoons in each district in Kagoshima Prefecture via LRM and NN", 2004. [11]

Kagoshima Prefecture has seen multiple typhoons. They damage power systems and cut power. To quickly restore electricity, one must predict the storm damage in each location. This article predicts damage in each Kagoshima district using a two-stage model. First, LRM (linear regression model), then NN (neural networks). This predictor can predict the number of typhoon-damaged distribution poles and wires. Actual data ensures the approach's effectiveness.

[6] Management of Industrial Accident Prevention and Preparedness" A Training Resource Package UNEP, vol. 1, pp. 55-97, June 1996.

Recent accidents throughout the world have exposed industrial hazards. Large and little mishaps are preventable. Accidents can be mitigated in several ways. Potential victims of large-scale incidents can be told how to respond to reduce dangers to themselves and property. APELL helps prevent or mitigate accidents. APELL stands for Local Emergency Preparedness. It's not a risk reduction programme, but good hazards communication encourages industry to decrease risks. APELL is a hazard communication technique that leads to collective action. Systematic integration of technical, administrative, legal, and infrastructure factors is required for comprehensive field programme management. Effective early public communication is a prerequisite for effective accident preparation. A well-informed community is the safest. UNEP holds regular APELL Seminar Workshops.

EXISTING SYSTEM

Prediction of damage caused by natural disasters and especially earth quakes lands under predictive analysis which is becoming a prominent area to study. A lot of research study has been done using fuzzy analysis and being done towards finding accuracy in predicting damage impact due to earth quakes.

Limitations of existing system (Problem)

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Fuzzy analysis was used in predicting impact of the damage caused by earth quake by considering seismic damage index as parameter. The average damage index has been produced by taking into account of adapted index and some impact factors. As the fuzzy analysis depends on mathematical calculations, require regular updates of conventions and machine learning can't be recognized and used. This state may affect accuracy.

To find best fitted algorithm with high accuracy various machine learning algorithms like Naïve Bayes, Random Forest, K-Nearest neighbors were used, in which Random forest got proved with high accuracy.

PROPOSED SYSTEM

To predict the extent of damage caused by an earthquake, machine learning can be used. In addition to identifying safe and unsafe buildings, it can also help predict damage-prone areas, reducing the risk of fatalities and injuries from earthquake aftershocks, and facilitating rescue efforts.

As Extreme Gradient Boosting may lead to high accuracy for smaller as well as fast for larger datasets, XGBoostalgorithm has been joined with Naïve Bayes, Random Forest, K-Nearest neighbors. XGBoost having the qualities like strewn and extendable, decision tree boosting can be done parallel along with tree pruning will lead to high accuracy. As XGBoost algorithm is the prominent machine learning library for ranking, classification and regression issues. For larger sets of data XGBoost algorithm fits best with high accuracy for same datasets as of remaining machine learning algorithms.

This work presents that the XGBoost algorithm has the highest accuracy in predicting the damage due to earthquakes, based on the F1 score and similarity score calculated for each of the four algorithms previously mentioned in this work. K-Nearest Neighbors has been observed to be the second most preferred algorithm for earthquake damage prediction.

DATA DESCRIPTION

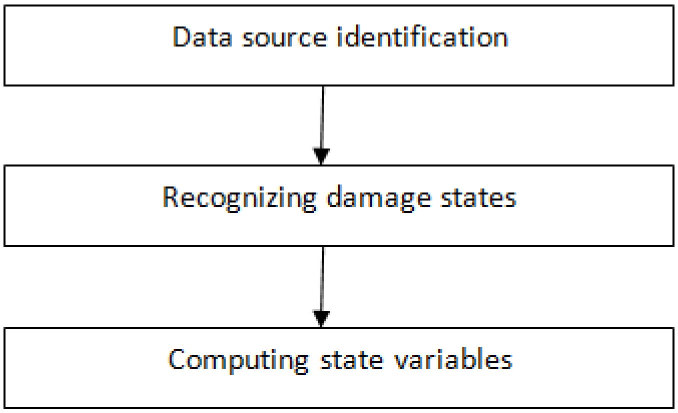

Fig.1. Data description flow diagram

The above diagram represents the 3 required steps in the process of organizing the data.

1. Identifying Data source.
2. Recognizing states of damage.
3. Computing state variables.

State variables are the measurable variables that hold the damage extent caused by earth quake.

The following are two main categories:

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- Structural variables [age, plinth area, number of floors, area of the structure]
- Non-Structural variables
  - String factors [Plan, Condition of the surface, foundation type, roof type, plan, position]
  - Boolean factors [secondary purpose true or false]

These variables feed required parameters in dataset attributes. As our study requires complete and valid data of earthquake like Occurrences, Reason for occurrence, Geographic location, Magnitude, Impact factor, Damage caused in-terms of different kinds property and life, Structure features, Is the damage repairable?, Is it feasible? Etc.

Such data in the form of dataset can be acquired from kaggle dataset about earthquake impact prediction and analysis. Acquired dataset must be maintained in a folder. This folder can be uploaded to the application. Uploading a folder can be done by using an event which can be triggered through a button click provided on the application user interface. Application user interface with required set of controls has been developed by importing tkinter libraries in python.

DATA SOURCE

Data Source contains four files:

a. Usage of the structure and ownership information.
b. Composition of the structure.
c. Train dataset.
d. Test dataset.

<u>Usage of the structure and ownership information</u>:

(Building_Ownership_Use.csv)

Information regarding building/structure and its location like ID of the building, ID of the district, MunicipalityID, WardID and Ownership information like status of ownership, count of families and does the building used for secondary purpose, if so for what purpose it has been used other than primarily such as hotel, rental, institution, school, industry, as health post, government office, police, others which contain boolean values 0 and 1.

For example, the following snippet shows:

- Building having building ID a3380c4f75 has not been used for secondary purpose.
- Building having building ID 6629c5ea196 has been used for secondary purpose as institution.

building_id	a3380c4f75	6629c5ea196
district_id	7	7
vdcmun_id	701	702
ward_id	70102	70206
legal_ownership_status	Private	Private
count_families	1	1
has_secondary_use	0	1
has_secondary_use_agriculture	0	0
has_secondary_use_hotel	0	0
has_secondary_use_rental	0	0
has_secondary_use_institution	0	1
has_secondary_use_school	0	0
has_secondary_use_industry	0	0
has_secondary_use_health_post	0	0
has_secondary_use_gov_office	0	0
has_secondary_use_use_police	0	0
has_secondary_use_other	0	0

Fig.2. Attributes and sample data_ Building_Ownership_Use.csv

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Composition of the structure: **(Building_Structure.csv)**

Information regarding building/structure like ID of the building, ID of the district, Municipality-ID, Ward-ID and composition information of the building such as number of floors before and after earthquake, age of the building, plinth area, height before and after earthquake, surface condition, foundation type, roof and floor type etc,.

building_id	a3380c503e	a338a4e653	a338a4e6b7	a338a4e71f
district_id	7	7	7	7
vdcmun_id	701	701	701	701
ward_id	70102	70103	70103	70103
count_floors_pre_eq	2	1	2	1
count_floors_post_eq	2	0	0	1
age_building	34	25	35	44
plinth_area_sq_ft	456	542	589	546
height_ft_pre_eq	18	9	18	9
height_ft_post_eq	18	0	0	9
land_surface_condition	Moderate slope	Moderate slope	Moderate slope	Moderate slope
foundation_type	Mud mortar-Stone/Brick	Mud mortar-Stone/Brick	Mud mortar-Stone/Brick	Mud mortar-Stone/Brick
roof_type	Bamboo/Timber-Light roof	Bamboo/Timber-Light roof	Bamboo/Timber-Light roof	Bamboo/Timber-Light roof
ground_floor_type	Mud	Mud	Mud	Mud
other_floor_type	TImber/Bamboo-Mud	Not applicable	TImber/Bamboo-Mud	Not applicable
position	Attached-1 side	Attached-1 side	Attached-1 side	Attached-1 side
plan_configuration	Rectangular	Rectangular	Rectangular	Rectangular
has_superstructure_adobe_mud	0	0	0	0
has_superstructure_mud_mortar_stone	1	1	1	1
has_superstructure_stone_flag	0	0	0	0
has_superstructure_cement_mortar_stone	0	0	0	0
has_superstructure_mud_mortar_brick	0	0	0	0
has_superstructure_cement_mortar_brick	0	0	0	0
has_superstructure_timber	1	1	1	1
has_superstructure_bamboo	1	1	1	1
has_superstructure_rc_non_engineered	0	0	0	0
has_superstructure_rc_engineered	0	0	0	0
has_superstructure_other	1	1	0	0
condition_post_eq	Damaged-Repaired and used	Damaged-Rubble unclear	Damaged-Rubble Clear-New building built	Damaged-Not used

Fig.3. Attributes and sample data_Building_Structure.csv

Composition data focus on the material used for construction of the building like is it composed of adobe mud, mud mortar stone, flag stone, cement mortar stone, timber, bamboo, has any super structure or not etc, and the condition of the structure after earthquake is determined with a string data like damaged-repaired and used / damaged and not used / damaged-rubble unclear etc,.

Train dataset: **(Train.csv)**

Training dataset was selected which is a part of entire dataset, based on each district_ID for example, district_id:7 complete data i.e number of records of district 7 are 4561 among these records around 60% records 2714 were considered for training with all parameters.

Some key attributes or fields were chosen to determine damage grade based on their values yes(1) or no(0) in corresponding attributes and were provide as training dataset for the selected ML algorithms through which training can be done. The following is the list of key parameters provided in training dataset:

area_assesed	Building removed	Exterior	Not able to inspect	Interior	Both (Repaired & used)
building_id	21e7f6b1edd	1f2bb88b361	2c2e47870c3	1c57247f12ae	1340abbb383
damage_grade	Grade 5	Grade 3	Grade 5	Grade 2	Grade 3
district_id	23	21	30	31	13
has_geotechnical_risk	1	1	1	1	1
has_geotechnical_risk_fault_crack	0	0	1	0	1
has_geotechnical_risk_flood	0	0	0	1	0
has_geotechnical_risk_land_settlement	1	0	1	0	1
has_geotechnical_risk_landslide	0	0	0	0	1
has_geotechnical_risk_liquefaction	0	0	0	0	0
has_geotechnical_risk_other	0	0	0	0	0
has_geotechnical_risk_rock_fall	0	1	0	0	0
has_repair_started	0	0	1	1	1
vdcmun_id	2330	2142	3036	3116	1323

Fig.4. Attributes and sample data_Train.csv

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The key parameter has_geotechnical_risk states that whether that structure has any risk because of its geographical location if so, identify the geotechnical risk like is there any possibility of landslide, fault crack, rock fall etc.

With the above training dataset each algorithm is trained and made ready for accepting testing dataset to predict damage grade and find accuracy score based on the above specified parameters.

Test Dataset: **(Test.csv)**

Dataset for testing was composed with around 40% i.e 1847 records of the whole dataset, based on district_ID for example, district_id:7 has complete data i.e number of records of district 7 are 4561. These 1847 records were considered for testing with all parameters except "damage grade" were given to individual algorithms to predict "damage grade" and thus finding accuracy score in predicting "damage grade" for the given set of parameters.

area_assesed	Building removed	Exterior	Building removed	Not able to inspect	Interior
building_id	a3eadcadd2	d32e9adbd6	94bb132807e	101bef02df4	b427d6d0a37
district_id	7	9	10	11	12
has_geotechnical_risk	1	1	1	1	1
has_geotechnical_risk_fault_crack	0	0	0	1	1
has_geotechnical_risk_flood	0	0	0	0	0
has_geotechnical_risk_land_settlement	0	0	0	1	0
has_geotechnical_risk_landslide	0	0	1	0	0
has_geotechnical_risk_liquefaction	0	0	0	0	0
has_geotechnical_risk_other	0	0	0	0	0
has_geotechnical_risk_rock_fall	1	1	0	1	0
has_repair_started	0	1	1	0	1
vdcmun_id	704	907	1022	1107	1238

Fig.5. Attributes and sample data_Test.csv

METHODOLOGY

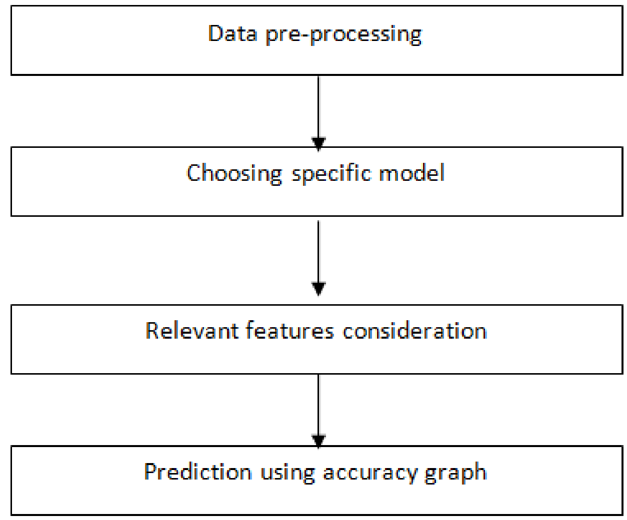

Fig. 6.Methodology flow diagram

Pre-processing:

Data pre-processing has been done through missing value imputation, normalization, conversion and partitioning. Municipality, District, ward and structure identifications are collectively used to identify a structure. These attributes were included to training data to determine damage grade of the building. Composition details are mostly string data which were transformed into their vector notation [0, 1, 2] using labeled encoding technique which is one of the pre-processing techniques in data-mining.

Once dataset has been imported, there is a need to perform effective data processing on the sample and extract the features. The dataset contains a collection of attributes describing earthquakes will be used for analysis in this research. The built-in functions in the pandas library for python were used for identifying the number of null and non-null values for each attribute.

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Data pre-processing is being done by following actions:

1. Data should be loaded to pandas.
2. Identify columns which are not useful.
3. Rows which are having missing values are dropped.
4. Missing data should be handled.
5. Formed data frame must be transformed to NumPY
6. Split processed dataset as training and testing datasets

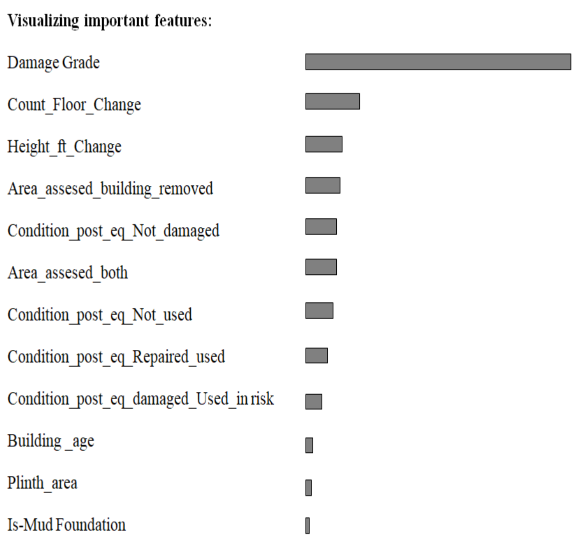

Fig. 7. Visualizing important features

Train and Test

Split the data into train and test data around 60:40 proportion. In which 60% of dataset will be allocated and provided to algorithms for training whereas 40% of dataset can be treated for testing. Such testing data can be used to compare the results after predicting to determine accuracy range. Training dataset will be used for training the model and testing dataset to check the performance.

Model Selection:

Wide varieties of machine learning algorithms are available to address classification problem. Identifying best fit algorithm among them for same data-set on a relevant argument will lead to evaluate them.

Combine the training using machine learning algorithms and establish a classification model. Where each algorithm will be given required dataset which should be used for training and testing, while performing training, testing, execution time and accuracy score.

Dataset received by XGBoost will undergo an effective strategy to train models one after another as weak learners collectively to form as a strong learner.

This evaluation can be done using F1 score with weighted average in accordance can be determined as follows:

$$F1 = \frac{2 * precision * recall}{precision + recall}$$

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

Here,

TP refers to True Positive, i.e. When the model rightly predicts a positive result.

FP refers to False Positive i.e. When the model wrongly predicts a positive result.

FN refers to False Negative i.e. When the model wrongly predicts a negative result.

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On executing machine learning classification algorithms on pre-processed data, the following results were obtained:

ALGORITHM	ACCURACY SCORE
Naïve Bayes	0.75127
Random Forest	1.0
K-NN	0.90516
XGBoost	1.0

Table 1. Accuracy Score for a specific and same data set

Prediction

Individual algorithms trained their models on the training dataset, then used test data for ultimate damage prediction and evaluation. Random Forest Classifier and XGBoost had the highest F1 score. In terms of dataset size and prediction time, XGBoost can be used.

RESULTS AND DISCUSSIONS

Based on the study of generated accuracy score, among chosen Naïve Bayes, Random Forest, K-NN and XGBoost machine learning algorithms, it is proved that XGBoost is having high accuracy when compared to remaining machine learning algorithms.

Even though Random forest gave high accuracy, XGBoost uses an effective strategy to train models one after another as weak learners collectively to form as a strong learner by using the following parameters:

Lambda -> Regularization parameter which reduces outliers of the prediction.

Gamma -> Threshold that defines auto pruning of tree thus controls over-fitting.

ETA -> Is the value ranging between 0.1-1.0 to determine how fast converge to next value (learning rate).

similarity score = (sum of residuals)^2/ (number of residuals+lambda)

Based on the similarity score, gain can be calculated by finding the difference between similarity scores after and before splitting:

Gain = similarity score after split - similarity score before split

XGBoost requires a parameter gamma to be compared with resulted gain to determine how aggressively decision tree is going to be split. If the gamma value is less than gain decision tree continuous to split. This technique is called auto pruning, which makes XGBoost algorithm more accurate. Higher gamma value makes the decision tree to split more aggressively and lower gamma value makes the decision tree to split less aggressively

New prediction = previous prediction + learning rate * output

Learning rate is ETA usually ranges from 0.1 to 1.0 in XGBoost algorithm. This is the way how models will be trained one after another to reduce residuals thus increasing accuracy.

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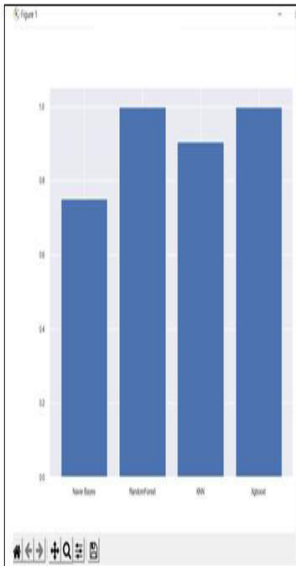

Fig. 8. Accuracy Graph

Accuracy of GaussianNB: 0.75127

Time consumed by NB: 56.397613525390625

Accuracy of RandomForestClassifier: 1.0

Time consumed by RF: 143.5710310935974

Accuracy of KNeighborsClassifier: 0.9051698347951203

Time consumed by KNN: 176.91002774238586

Accuracy of XGBClassifier: 1.0

Time consumed by XGBoost: 84.49493193626404

Fig. 9. Accuracy with time consumption

The produced results are generated in the following configuration:

Device name	: LAPTOP-0OLOBENS
Processor	: AMD Ryzen 5 4600H with Radeon Graphics 3.00 GHz
Installed RAM	: 8.00 GB (7.36 GB usable)
System type	: 64-bit operating system, x64-based processor
Number of active Applications	: 02
Edition	: Windows 10 Home Single Language

CONCLUSION:

Identification of effective machine learning algorithm for high accuracy towards analysis and prediction of earth quake impact has been done among naïve bayes, random forest, K-nearest neighbors and XGBoost. As a result XGBoost algorithm showed high accuracy for small as well as fast for larger datasets due to the ability of tuning its hyper parameters like eta and gamma.

The default value of eta is 0.3 and it can range from 0.1 – 1.0, by decreasing the value of eta results high accuracy for desired data sets. The default value of gamma is 0, increasing the value of gamma controls the over-fitting of the model and results in pruning of the decision tree.

This study can be extended towards wide variety of datasets available to find high accuracy for corresponding prediction analysis while generating result as such. Inclusions and updates can also be considered as a future scope.

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BIOGRAPHY

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P. SREENIVASULU Assoc. Professor DEPARTMENT OF Computer Science and Engineering, Narayana Engineering College, completed his M.Tech in Computer Science and Engineering from Nagarjuna University and SET & NET qualified. He has got 25 years of teaching experience. He has

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attended many Faculty Development Programs and Workshops.