

Predicting Road Crash Using Ensemble Learning

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ABSTRACT— The number of vehicles increasing on the road inthe recent years which leads to increase in the number ofaccidents. Accident prediction and prevention is the majorchallenge faced by the government / transport department.TheObjectiveofthissystemistodevelopa machinelearningmodelforreal-

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timeaccidentforecastingbycomparing supervised algorithms with mean value of votingclassifier results. Recent technologies like automated trafficcontrol signals and IOT based GPS Technology helps inpreventing accidents on the road. The Machinelearni ngalgorithms has been implemented to predict the occurrenceofaccidentsontheroad.Ensemblelearning methodisoneof the best method for accident forecasting and finding thebestroadselection. Thissystem

isproposedtocompareensemblelearningalgorithmwit hotheralgorithmslikesupervisedmachinelearningalg orithmsuchaslogistic regression, decision tree. random forest, and support vectorclassifier, K nearest neighbor and Naive Bayes. EnsembleLearning better produces predict performance compared to asinglemodel.InEnsemblelearningtechnique, various models will be combined and the best prediction result willbe found. The comparative analysis helps prove to that theensemblelearningalgorithmprovideshighaccurac yofresults than other model. The voting classifier method

inensemblelearninghelpstodocomparativeanalysisa ndthere by forecast accident and to find the best road. Datasetof previous accident reports available in government websitehas been used as input data to find the best road and topredictthe accidents. **Keywords:**MachineLearning,EnsembleLearning,Pr edictionofAccuracy

I. INTRODUCTION

Machine learning is to predict the future from past data.Machine learning (ML) is a typeof artificial

intelligence(AI)thatprovidescomputers with the abilit ytolearnwithoutbeingexplicitlyprogrammed.Machin elearningfocuses on the development of Computer Programs that canchange when exposed to new and the basics data of MachineLearning, implementation of a simplemachin elearningalgorithm using python. Process of training and predictioninvolves use of specialized algorithms. feed the It trainingdatatoanalgorithm, and the algorithm uses thist rainingdata to give predictions on a new test data. Machine learningcan be roughly separated in to three categories. There are supervised learning, unsupervised learning and rein forcement learning. Supervised learning program is bothgiven the input data and the corresponding labeling to learndatamustbelabeledbyahumanbeingbeforehand. Unsupervisedlearningisnolabels. It provided to the lear ningalgorithm. This algorithm must figure out the cluste ringoftheinputdata.Finally,Reinforcementlearning dynamicallyinteracts with its environment and itreceiv espositiveornegativefeedbackto improveitsperformance.

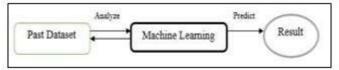


Fig.1:ProcessofMachinelearningmethod



Roadandtrafficaccidentsareunsureandunde terminable incidents and their valuation calls for theexpertiseofthefactorsaffectingthem.Roadandtraff icaccidents are defined by a set of variables which can

beusuallyofdiscretenature. The essential difficulty int heanalysis of coincidence records is its heterogeneous

nature.Classificationismachinelearningtechniquetha tcanbeusedasaninitialtasktoobtainvariousgoalsandth eclassificationcategorizetheaccidentdataintodifferen tcategories.

SequentialEnsemblelearning(Boosting):Bo osting is a machine learning ensemble metaalgorithm

forprincipallyreducingbias,andfurthermorevariancei nsupervisedlearning,andagroupofmachinelearningal gorithms that convert weak learner to string ones. Boostingisameta-

algorithmwhichcanbeviewedasamodelaveragingmet hod.Itisthemostwidelyusedensemblemethod and one of the most powerful learning ideas. Thismethod was originally designed for classification but it canalsobeprofitably extended to regression. The origin alboostingalgorithmcombinedthreeweaklearnerstog enerateastronglearnerandsequentialensemblemetho dswherethebaselearnersaregeneratedsequentially.

ParallelEnsembleLearning(Bagging):Baggingisama chinelearningensemblemeta-

algorithmintendedtoimprovethestrengthandaccurac yofmachinelearningalgorithms used in classification and regression purpose. Itadditionally diminishesfluctuation of data(variance)andhelp to over-fitting. Bagging Bootstrap from or Aggregationis a powerful, effective and simple ensemble method. Themethod uses multiple versions of a training set by using thebootstrap, i.e. sampling with replacementand tit can be used with any type of model for classification or regression.Bagging is only effective when using unstable (i.e. a smallchange in the training set can cause a significant change in the model) non-linear models and parallel ensemble methodswherethebaselearnersaregeneratedinparalle 1.

StackingandBlending:Stacking

isawayofcombiningmultiplemodelsthatintroducesth econceptofa Metalearner. Itislesswidelyusedthanbaggingandboosting.Unlikeb aggingandboosting,stackingmaybeusedto combine models of different types.Stacking is concernedwithcombiningmultipleclassifiersgenerat edbyusingdifferentlearningalgorithmsonasingledata setwhichconsistsofpairsoffeaturevectorsandtheircla ssifications.

This technique consists of basically two phases, in the firstphase, a set of base-level classifiers is generated and in thesecondphase, a metalevel classifier is learned which combines the outputs oft hebase-level classifiers. Blending is technique where we can do weighted averaging offinal result.

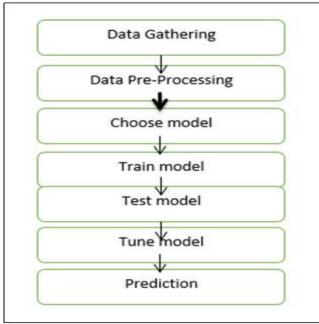


Fig.2:ProcessofDataflowdiagram



Machine learning needs data gathering have lot ofpast data's. Datagathering have sufficient historical dataand raw data. Before data pre-processing, raw data can't beuseddirectly.It's usedtopreprocess then,whatkind of algorithmwithmodel.Training and testing this model working and predicting correctly with minimumerrors. Tuned model involved by tuned time to time with improving the accuracy.

II. SYSTEMMODEL

Ensemble learning helps improve machine learning

resultsbycombiningseveralmodels. This approachall owstheproduction of better predictive performance compared to asingle model and it is the art of combining diverse set oflearners together to improvise on the stability and predictivepower of the model. In the world of Statistics and MachineLearning, Ensemble learning techniques attempt to make theperformance of the predictive models better by improving their accuracy. Ensemble Learning is a process using whichmultiplemachinelearningmodelsarestrategical lyconstructed tosolve a problem.

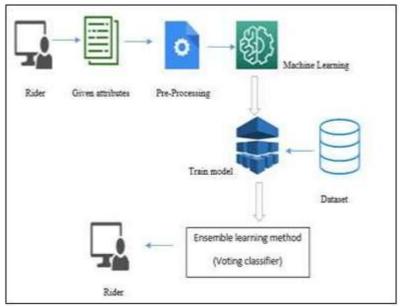


Fig.3:Systemarchitecturediagram

Max Voting: The max voting method is generallyused for classification problems. In this technique, multiplemodels are used to make predictions for each data point. Thepredictions by each model are considered as a 'vote' and thepredictions which we get from most of the models are usedasthefinalprediction.

Averaging: Similar to the max voting technique, multiple predictions are made for each datap oint in averaging. In this method, we take an average of predictions from all the models and use it to make the final prediction. Averaging can be used for making predictions in regression problems or

while calculating probabilities for classification problems.

WeightedAverage:Thisisanextensionoftheaveraging method. All models are assigned different weightsdefiningtheimportanceofeach modelforprediction.

A.PreparingtheDataset

The dataset is now supplied to machine learning model onthe basis of this data set themodel is trained. Every newdatadetails filledat the timeof application form acts asatestdata set.

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Variable	Description
Accidentoccurs_Date	Dateofaccidentoccurs
Light_Cond	Roadlightcondition
Weathconds	Placeofweatherconditions
Mod	Vehicledriver orpedestrian
Age	Ageofdrivers

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Vehicle_type	Typeofvehicle
Route1,2,3	Multitrafficroutes
Locations	Placeofaccident
cctv_footag	videosisonoroffcondition

Table1: Detailsofgivendataset

III. METHODOLOGY

A. DataValidationandPreprocessing

tativeofthepopulation, you may not need the validation techniques. However, in real-world scenarios, to

Validation techniquesin machinelearning are usedto getthe error rate of the Machine Learning (ML) model, which can be considered as close to the true error rate of th edataset. If the data volume is large enough to be represen workwithsamplesofdatathatmaynotbeatruerepresent ative of the population of given dataset. To findingthe missing value, duplicate value and description of datatypewhether itisfloat variableor integer.

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Fig.4:Givendataframe

Importing the library packages with loading

givendataset.Toanalyzingthevariableidentificationb ydatashape, data type and evaluating the missing values, duplicatevalues.A validation datasetisasampleof data heldbackfrom training your model that is used to give an estimate ofmodel skill while tuning models and procedures that you canuse to make the best use of validation and test datasets

whenevaluatingyourmodels.Datacleaning/preparing byrenamethegivendatasetanddropthecolumnetc.toa nalyze the uni-variate, bi-variate and multi-variate process.The steps and techniques for data cleaning will vary fromdataset to dataset. The primary goal of data cleaning is todetect and remove errors and anomalies increase the valueofdata to inanalyticsanddecisionmaking. Pre-processing refers to the transformations appliedtoourdatabeforefeedingittothealgorithm.Dat aPreprocessing is a technique that is used to convert the rawdata into a clean data set. In other words. whenever the dataisgatheredfromdifferentsourcesitiscollectedinra wformat which is not feasible for the analysis. To achievingbetter results from the applied model in Machine Learningmethod ofthedata hastobeinapropermanner.

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Fig.5:Pre-processeddataframe



B. ToTrainAModel

ofVisualizationbyGiveAttributes

Data visualization is an important skill in applied

statisticsandmachinelearning.Statisticsdoesindeedfo cusonquantitativedescriptionsandestimationsofdata. Datavisualization provides an important suite of tools for gainingaqualitativeunderstanding.Thiscanbehelpful whenexploring and getting to know a dataset and can help withidentifying patterns, corrupt data, outliers, and much more.With a little domain knowledge, data visualizations can beusedtoexpressanddemonstratekeyrelationshipsinp lots

andchartsthataremorevisceralandstakeholdersthanm easures of association or significance. Data visualizationand exploratory data analysis are whole fields themselvesand it will recommend a deeper dive into some the booksmentioned atthe end.

DataVisualizationAftertheclassificationandregressi onprocessthepredictedresultsarevisualizedingraphic al or tabular format for better understanding of theusers.Wecanalsogetthesummaryoftheresultsinnu merical format. Sometimes data does not make sense untilit can look at in a visual form, such as with charts and plots.Being able to quickly visualize of data samples and others isan important both in applied statistics skill and in appliedmachine learning. It will discover the many of plotsthatyouwill types needtoknowwhenvisualizingdatainPython.

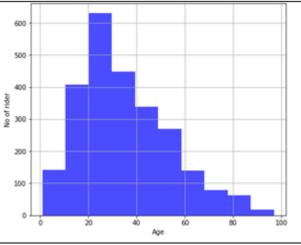


Fig.6:Ageofdistributionofeachriders

Evenbeforepredictivemodelsarepreparedo ntrainingdata,outlierscanresultinmisleadingrepresen tationsandinturnmisleadinginterpretationsofcollecte ddata.Outlierscanskewthesummarydistributionof attributevalues in descriptivestatistics likemean andstandarddeviationandinplotssuchashistogramsan dscatterplots,compressingthebodyofthedata.Finally, outliers can represent examples of data instances that arerelevant to the problem such as anomalies in the case offraud detection and computersecurity.

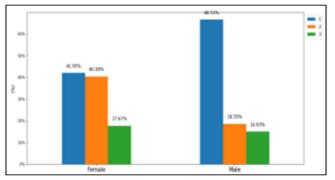


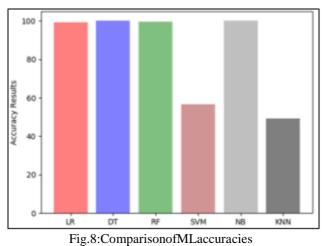
Fig.7: Accidentpredictionbyroutes



It couldn't fit the model on the training data andcan't say that the model will work accurately for the realdata. For this, we must assure that our model got the correctpatterns from the data, and it is not getting up too muchnoise.Crossvalidationisatechniqueinwhichwetrainour model using the subset of the data-set and then evaluateusingthe complementarysubset of the dataset.

C. ComparisonofMachineLearning AccuracyResults

Itisimportanttocomparetheperformanceof multipledifferentmachinelearningalgorithmsconsist entlyanditwill discover to create a test harness to compare multipledifferent machine learning algorithms in Python with scikit-learn. It can use this test harness as a template on your ownmachinelearningproblemsandaddmoreanddiffer entalgorithmstocompare.Eachmodelwillhavediffere ntperformance characteristics. Using resampling methods likecross validation, you can get an estimate for how accurateeach model may be on unseen data. It needs to be able to usethese estimates to choose one or two best models from thesuite of models that you have created. When have a newdataset, it is a good idea to visualize the data using differenttechniquesinordertolookatthedatafromdiffe rentperspectives. The same idea applies to model selection. Youshould use a number of different ways of looking at theestimated accuracy of your machine learning algorithms inorder to choose the oneor twotofinalize.Away to dothis is to use different visualization methods to show theaverageaccuracy, variance and other properties of th edistributionofmodel accuracies.



D. ImplementationofVotingClassifierAlgorith

Voting is one of the most straightforward Ensemble learningtechniques in which predictions from multiple models arecombined. Themethodstarts with creating two ormoreseparate models with the same dataset. Then a Voting based Ensemble model can be used to wrap the previous models and aggregate the predictions of those models.

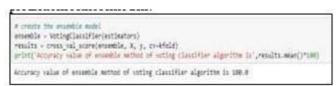


Fig.9: Accuracyresultofvotingclassifier

AftertheVotingbasedEnsemblemodeliscon structed, it can be used to make a prediction on new data.The predictions made by the sub-models can be assignedweights. Stacked aggregation is a technique which can beused to learn how to weigh thesepredictionsinthebestpossibleway.Inthefieldofmachinelearningandspecificallytheproblemofstatisticalclassification,aconfusionmatrix,alsoknownasanerrormatrix.Aconfusion matrix is a table that is often used to describe



theperformance of a classification of ensemble voting classifiermodel on a set of test data for which the true values areknown. It allows easy

identification of confusion betweenclassesofaccidentoccurred and notoccurred accident.

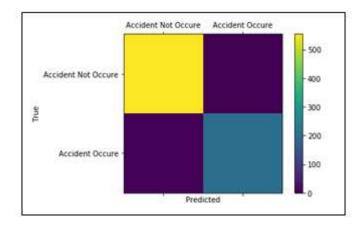


Fig.10:Confusion matrixof votingclassifier

Aconfusionmatrixisasummaryofprediction resultsonaclassificationproblemandthenumberofacc ident not occurred and accident occurred predictions aresummarized with count values and broken down by eachclass. The confusion matrix shows the ways in which yourclassification model is confusedwhen itmakes predictions.It gives us insight not only into the errors being made by aclassifier but more importantly the types of errors that arebeing made.

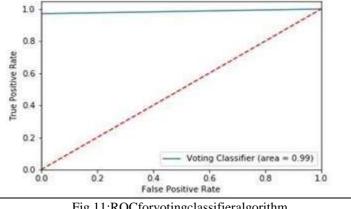
DefinitionoftheTerms:

- Positive(P):Observationispositive(Accidentnot occurred).
- Negative(N):Observationisnotpositive(Acciden toccurred).
- TruePositive(TP):Observationispositive, and isp redicted tobe positive.
- FalseNegative(FN):Observationispositive,butis predicted negative.

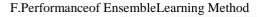
- TrueNegative(TN):Observationisnegative,andi spredicted tobe negative.
- FalsePositive(FP):Observationisnegative,butis predicted positive.

To predicting the probability of a binary outcome is the Receiver Operating Characteristic curve, or ROC curveand it summarize the trade-off between the true positive rateand false positive rate for a predictive model using different probability thresholds.Precision-Recall curvessummarizethe trade-off between the true positive rate and the positivepredictivevalueforapredictivemodelusingdif ferentprobability thresholds. ROC curves are appropriate when the observations are balanced between each class, wher

recallcurvesareappropriateforimbalanceddatasets.



easprecision-





E. PerformanceofMachineLearningParameters

Parameter	LR	DT	RF	SVM	NB	KNN
Precision	0.9	1	1	0	1	0.5
Recall	1	1	1	1	1	0.7
F1-Score	1	1	1	0.7	1	0.6
Sensitivity	1	1	1	1	1	0.7
Specificity	0.9	1	1	0	1	0.2

F.Performanceof EnsembleLearning Method

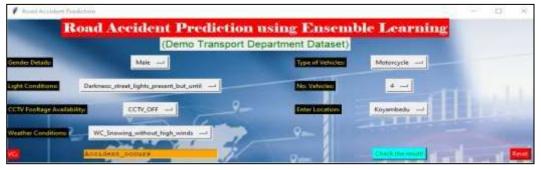
Parameter	VotingClassifier
	_
Precision	0.99
Recall	1
F1-Score	0.99
Sensitivity	1
Specificity	0.97
TP	200
TN	554
FP	0
FN	6
TPR	0.97
TNR	1
FPR	0
FNR	0.02
PPV	1
NPV	0.98
Accuracy	100

G.TestingResults

Road	Accident Predicti	ion using Ensemb	le Learning	
	(Demo Transpo	ort Department Dataset)		
nder Details	None	Type of Vehicles	None	
ht Conditions	None	Na. Vehicler	None	
TV Footlage Availability	None	- Enter Location	Nore	
ether Conditions	None -	9-1-1		



2) Output: Test-01:



Test-02:

Read Acodest Per		1742 AT 1742 AND 1742	- 0	×
R	oad Accident Prediction		de Learning	
	(Demo Transport De	epartment Dataset)		
Gender Details	Female	Type of Vehicles:	Scooter	
ght Conditions	Darkness_no_street_lighting	No. Vehicles	2	
CTV Foottage Availabil		EnterLocation	Egmore	
eather Conditions a	WC_Snowing_without_high_winds -	9		
	No_Acoldents	- 1	Check the result	leset

IV. CONCLUSION

Theimproved accuracy and implementation is make the proposed method to help the transport department make adiagnosis before the accidents and the accuracy result is voting classifier algorithm by comparing super vised machine learning method.

V. FUTURE WORK

In future, I would like to discover the automate this processby show the prediction result in web application or desktopapplicationandtooptimizetheworktoimplem entinArtificialIntelligence environment.

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