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ANOVELAPPROACHFOREMPLOYMENTPROJECTION

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ABSTRACT: Acampusplacementpredictio n system is developed to calculatethe possibility of a student getting jobs in acompany through campus placements. Themodeltakesmanyparameterswhichcanb eused to get an idea about the skill level ofthestudent.Whilesomedataaretakenfromt hecollegelevellikeacademicperformance, CGPA, Internships, Stream,Backlogsetc.,othersareobtainedfro mtestsconductedintheplacementmanageme ntsystem.Combiningthesedatapoints, the model is to accurately predict ifthe student will or will not be placed in acompany. Regression analysisisused inplacement prediction to determine the linkbetweennumerousvariables,includinga cademic achievement, skill set, prior jobexperience,andthelikelihoodofbeinghire dbyafirm.Decisiontreesareemployedinthepl acementpredictionscenariotosimulatethehir ingprocess decision-makingofbusinesses.Neuralnetworks are used in placement predictiontorepresenttheintricateconnectio nsbetween many elements that influence thelikelihoodof beinghired byafirm.

INTRODUCTION

Inordertoanticipateplacement,informat ion is gathered from a varietyofsources,includingacademictra nscripts,resumes,andpriorjobexperienc e.Afterthat,thisdataiscleansed and preprocessed to removeanydiscrepanciesormistakes.Af terbeing cleaned, the data is divided intotwocategories:trainingdataandtesti ngdata.Themachinelearningalgorithm is trained using the trainingdata, and its effectiveness is assessedusing the testing data. The system istaughtusingavarietyofmethods,includ ingneuralnetworks,decisiontrees,andre gression analysis.

Mainpurposeofthisprojectistopredictthestudentplacementpredictionusingmachinelearning.Hence,thiswillhelpstudentsforbetterplacement.Forinstitutions,itwillhelptobuildbetterplacementsandacademicrecordsaswellto attract new admissions as well as togetreputation.

The primary objective of campus hiring istoidentifyandhiretalentedindividualswho are abouttograduatefromtheeducationalinstitutions.So,withthehelpofmachinelearningalgorithmswecaneasilyknowaboutthestudentswhoaregoing to b

PROPOSEDSYSTEM

The project object is designed and thedata is collected by the college, aftercollecting the data we divided the datainto training and testing datasets. Thedataisseparatedintodependentvariablesandindependentvariablesandthenth eoutliers areremoved.

- Modelistrainedwithtrainingdata.
- Themodelisfine-tunedandthetrainingdataisfurtherclassifiedaccordingtotheparametersspecifiedinthemodel.

After training the model the testingdatasetwhichwasstoredearlierisprocessedtothemodelfortheprediction

advantages

- Inastudentplacementprediction project,youcoulduseSVMforits effectivenessinhigh-dimensional spacesif youhavelargenumberoffeatures .
- Decision trees might be usefulfortheirinterpretability,especiallyifyouwanttoexplainthe modeltostakeholders.
- Logisticregressioncouldbehandyforprovidingprobabilitiesofplacementoutcomes, while random forestcould offer robustness againstoverfittingandinsightsintofeatureimportance.
- Theaccuracyismorewhenweareusing SVM.

LITERATURESURVEY

WiltonandK.Y.Lawconductedastudytopredictsuitablecourseforthestudents,basedontheirbehaviorusingNeuralNetworkTechnique. Tensorflowengineincludesnumberofintermediatenodeandnumberofdeeplearninglayers areadjustedandcompared.

Itseemslikeyou'resummarizingastudycondu ctedbyWiltonandK.Y.Lawwheretheyusedn euralnetworktechniques,particularlyutilizin gTensorFlow,topredictsuitablecourses for students based on theirbehavior.Theylikely experimented withadjusting thenumber of intermediate nodesand the depth of the neural network layersto compare theireffectivenessinpredictingsuitablecourse s.Dr. A Padmapriya (November 2012) Datamining algorithm Decision TreeInductionis best when compared to Naive BayesianClassifier according toClassificationAccuracymisclassific ationRate,Speed&SizeonstudentsPersonalD ata, Precollegedata

& UnderGraduation DatatopredictHigherEducationAdmissibi lity.

Dr.APadmapriya'sstudyinNovember2012c omparedtheperformanceofthedataminingal gorithmDecisionTreeInductionwiththeNaiv eBayesianClassifier.Thecomparisonwas based on several criteriaincluding Classification Accuracy,MisclassificationR ate,Speed,andSizeofthemodels.Thedatasetu sedinthestudycomprisedstudents'PersonalD ata,Pre-collegedata,andUndergraduationData, withtheaimofpredictingHigherEducationA dmissibility.

nimesh.G al, 2016 have proposed a systemto predict the probability of astudent beingplaced using k nearest neighbour classifier.EuclideanDistanceinusedasadista ncemeasure.Thedatasetinvolvesacademichi storyofastudentsuchas10thpercentage,12th percentage, aggregate of engineeringscores and number of backlogsFurther postprocessingisdoneusingscoresofTechnic alskillsCommunicationskills,AnalyticalSki lls andas wellasTeamworkscoreareused.

Animesh.Gandcolleagues'systemproposedi n2016aimstopredicttheprobabilityofastude nt being placed in a job or internship usingthek-nearestneighbor(k-NN)classifier.Thesystem incorporates various aspects ofastudent'sacademichistory,includingtheir 10thpercentage,12thpercentage,aggregates coresofengineeringcourses,andthenumbero fbacklogs.

In addition to academic factors, the systemconsiders post-processing byincorporatingscoresrela tedtotechnicalskills ,communicationskills,analyticalskills,andtea mwork.Theseadditionalscoresofferamore holisticassessment of students'

capabilitiesbeyondtheiracademicperformancealone.

RELATEDWORK

Employmentprojectionprojectsusingmachinelearningcanbeeconomicallyfeasibleifimplementedproperly.Herearesomefactorstoconsiderregardingtheeconomicfeasibilityofsuchaproject:

Data Availability and Quality: Theavailabilityandqualityofhistoricalemploymentdataarecrucialfortrainingmachinelearningmodels.Ifhigh-quality data is readily available or canbecollectedata reasonable cost,itenhancesthefeasibilityoftheproject.

Model Development Costs:Developingmachinelearningmodelscanrequiresignificantupfrontinvestmentintermsofexpertise,infrastructure,andtime.However,theavailabilityof open-sourcelibrariesandframeworks,along with cloud computing services, hasloweredthebarrierstoentryinthisfield

Model Training and Maintenance:Once developed, machine learning modelsrequireperiodicupdatesandmaintenancetoremain accurate and relevant. The cost ofretraining modelsand updatingalgorithmsshouldbefactoredintotheoveralleconomicfeasibility.

AccuracyandPerformance:Theaccuracy and performance of the machinelearningmodels in predicting employmenttrends play a crucial role in determiningeconomic feasibility.Higher accuracy canleadtobetterdecision-makingandpotentiallysignificantcostsavingsorrevenuegeneration.

Return on Investment (ROI):Economicfeasibilityultimatelydependsonwhether thebenefits derived from theemploymentprojectionproject outweighthe costs incurred.Thesebenefitscouldincludemoreefficientworkforceplanning,reducedhiringcosts,improvedresourceallocation,andbetterstrategicdecision-making.

MarketDemand:Assessingthemarket demand for employment projectionsolutions andpotential revenue streams isessential. Organizations may be willing toinvest in such solutions iftheysee tangiblebenefitsintermsofcostsavingsorcompetitiveadvantages.

Regulatory and EthicalConsiderations: Compliance with dataprivacy regulations

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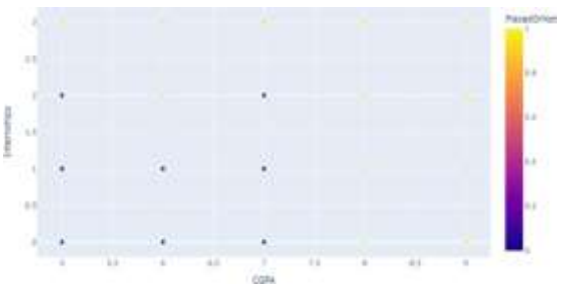
affecting the economicviabilityoftheproject.

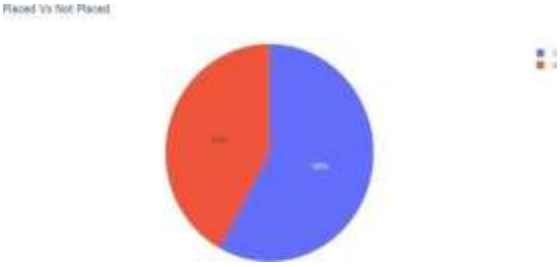
****Scalability**:** The ability toscaletheemployment projectionprojecttohandlelargerdatasetsorserveagrowingnumberofusersisimportantfor long-term economic feasibility.Scalabilityensuresthattheproject canadapttochangingbusinessneedsandmarketconditions.

SAMPLE RESULTS

	Age	Gender	Stream	Internships	CGPA	Hostel	HistoryOfBacklogs	PlacedOrNot
0	22	Male	Electronics And Communication	1	8	1	1	1
1	21	Female	Computer Science	0	7	1	1	1
2	22	Female	Information Technology	1	6	0	0	1
3	21	Male	Information Technology	0	8	0	1	1
4	22	Male	Mechanical	0	8	1	0	1

	Age	Gender	Stream	Internships	CGPA	Hostel	HistoryOfBacklogs	PlacedOrNot
975	21	Male	Information Technology	0	6	0	1	1
1406	22	Male	Civil	0	7	0	1	0
2482	22	Male	Mechanical	1	6	0	0	0
519	21	Male	Computer Science	1	8	0	0	1





CONCLUSION

Thelikelihoodthatastudentwillbehiredbyafirm maybepredictedusingplacementpredictionutilizingmachinelearning techniques. The application ofmachinelearningalgorithmsoffersamore data-drivenand objectiveapproachtothehiringprocess,allowingbusinessestofindpotentialapplicantswhowouldhavegoneunnoticedusingconventionalhiringtechniques.Machine learning isbecomingmoreandmoreprevalentacross a wide range of sectors,andplacement prediction usingmachinelearningalgorithmsispoisedto become a crucial toolinthehiringprocess.

REFERENCES

[1] Liu,Yang,etal."TheApplicationofMachinelearningTechniques in CollegeStudentsInformationSystem."2018InternationalConferenceonComputerScience,ElectronicsandCommunicationEngineering(CSECE2018).AtlantisPress,2018.

[2] Ishizue,Ryosuke,etal."Studentplacementandskillrankingpredictorsforprogrammingclasses usingclassattitude,psychologicalscales,andcodemetrics."ResearchandPracticeinTechnologyEnhancedLearning13.1(2018):1-20.

[3] Ahmed,S.,Zade,A.,Gore,S.,Gaikwad,P.,Kolhal,M.“PerformanceBasedPlacementPredictionSystem.”IJARIIE-ISSN(O)-4(3)2018:2395-4396.

[4] Manikandan, K.,Sivakumar,S.,Ashokvel,M.“A Classification Model forPredictingCampusPlacementperformanceClassusingDataMiningTechnique”InternationalJournalofAdvanceResearchinScienceandEngineering7(6)2018:29-38.

[5] Gilbert,Noah."PredictingSuccess:anApplicationofMachinelearningTechniquestoStudentOutcomes."InternationalJournalofMachinelearning&KnowledgeManagementProcess(IJDKP)7.22017:1-20.

[6] Rathore,RaviKumar,and J.Jayanthi."StudentPredictionSystem for PlacementTrainingusingFuzzyInferenceSystem."ICTACTJournalonSoftComputing 7.3(2017): 1443-1446.

[7] Nichat, Ankita A., and DrAnjali B. Raut. "Predicting andAnalysis of StudentPerformanceUsingDecisionTreeTechnique."InternationalJournal5 (2017):7319-7328.

[8] Suganthi, G., Ashok, M.V.“UniqueMachinelearningApproach to PredictPlacementChance.” InternationalJournal of Engineering Sciences&ResearchTechnology6(3)2017:263-269.

[9] Patel,T.,Tamrakar,A.“DataMiningTechniquesforCampus PlacementPredictioninHigherEducation.”IndianJ.Sci.Res.14(2)2017:467-471.

[10] Raut,A. B., Nichat, M.A. A.,Studentsperformancepredictionusingdecisiontree.Int.J.Comput.Intell.Res.13(7)2017:1735–1741.