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Artificial Intelligence Aided Innovation Education Basedon Multiple Intelligence

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ABSTRACT

The study of educational innovations has attracted increasing attention from academics around the world. Educationalinnovationproposestheimplementationofnewapproachesorpracticesthatarebeneficialandmakeanimpactonindividualsor academic communities. The current educational model of many designed for this generation of "digital natives". For thisreason, face the challenge of building teaching strategies that generate meaningful educational experiences. This researchseekstoaddressthisissuethroughasystematic mappingthatincludesempiricalprocessthatstudyinnovationsineducationalpractices.Aqualitativeandquantitativeapproachwasappliedusingafour-stageresearchmethodologytoevidenceinnovation in higher education. After employing the selected methodology and applying all the exclusion criteria, related tothe topic were identified. The proposed system using hybridization of linear vector quantization algorithm of learning, thecontext of learning, the role of the teacher, the role of the learner, and the performance improved and testing accuracy high.The meta-heuristic models to assess the performance of the students, then hybridization of linear vector quantization modelfor predicting the educational results and employability chances of the students is designed and developed an Ant ColonyOptimization (ACO) with feature subsetselection and RandomForest(RF)model forclassifying educationalDM.

Keyword:RFModel,AntColony Optimization,Hybridization ofLinearVectorQuantization Algorithm.

I. INTRODUCTION

Education is a complex social, cultural and ethicalprocess designed in a social or cultural context. It is relatedwith social structures, cultural environments, values andideas of people, society and the government. All thesefactorsaredynamic.Byallthesedefinitions of teachinghasbeen changing depending on the time, place, and society.A good teaching programmer may be designed to affectmaximum teaching and learning. Teaching has been oneof the oldest and most respected professions in the worldandtheteachersarethekingpinsofeducationalsystem.Itis the most influential profession in society. It is said thatteaching has acquired a status of profession because theneedforteacherandhiseducationandteachinghave beenimperative all these days. It is always a dynamic activity.It unfolds the world of knowledge and information andexperienceanderudition.Thepersonalityoftheteacherisasignificantvariableintheclassroom.Itissaidthat teachersaffecteternity.

NeedforTeacherEducation

Trainingisessentialforeveryteacher.Atrainedteacher can do more than untrained teachers. Demand ofprofession, the objective and expectations from a teachercertify the need of teacher training. Many skills are neededto communicate the information effectively such as theskillofquestioning,illustrating,demonstrating,explainingandtheskilloflogicallysequencingthesubject matter.Teachingisnotonlyconfinedtoimpartknowledgeofsubjectmattertoothers.Inawiderperspective,teaching aims at an all-round development of personality.Skills or attitudes can be developed through systematictraining.

MACHINELEARNING

AnMLmodelisdefinedasacomputer-intensivemechanismandappliesre-samplinganditerativemethodologiesforclassification approaches.MLapproaches are considered with optimal subset selectionand eliminate the issues of classical classifiers like over-fitting as well as distributional demands of parameters.ML technologies that have emerged in computer sciencewithlogicandbasicmathematics,statisticsasMLapproaches do not estimate the group features rather it isinitialized with an arbitrary group separator and tunesfrequentlytillsatisfyingtheclassificationgroups. MLexaminesthetuningvariablesandindividualMLfunctionsbecameunstable,whichmakesasuitableprocess. As the non-statistical nature is embedded, theseapproaches can apply the data in variousformats likenominaldatathatgeneratesmaximumclassificationaccuracies.

II. LITERATURE SURVEY REVIEW OF EXIST IN GEDM TECHNIQUESFOR HE STUDENTS

The EDM and Learning Abilities enable the learninginstitutions in overcoming these challenges by predictingthenumberofgraduatesandplacementsandtherebytaking the right decisions at right time to increase thisnumber. (Ji et al., 2018) [1]. DM helps to transform everymodelintodatasuchaslearningobjectives,learningactions, learning priority, participation, competitiveness,functions, as well as accomplishment tend from student'sparticipationfordifferentlearningeventsastheeducational decision-makers apply the predefined data.Recently, DM and ML models have been employed ineducational data, offering some solutions to the above-mentionedissues(Xingetal.,2019) [2].MLalgorithmhastried to follow the processes by studying and modelingthem computationally, and is commonly classified intotwo approaches: supervised learning (classification) andunsupervised learning (UL) (clustering), which are alsoknownaspredictiveanddescriptive,correspondingly(Rao et al., 2021) [3].
Thekeyobjectiveofthisstudyistwo-fold(delCampoetal.,2020)initially,comparetheestimationin2subjectslike Business Administration Degree among Finland andSpainand, secondly, test the factors like gender, age,subject,students'inspiration,orprioritieswhichaffectthestudent assessment. In (Sarra et al., 2019) the main aim isto estimate the application of specific latent class model,Bayesian Profile Regression for identifying the studentspronetodropout.Byassumingthestudents'performance,motivationandresilience,it enables tomakestudentsprofiles with maximum risk of academics. The real-timesample depends upon the data gathered by online queriesby UG studentsof anItalian University.
EDM and Learning Analytics (LA) are employed todefineandapplyDMmodelsinthenextlevelsofeducationgivenby(VanBarneveldetal.,2021) [4].It provides a systematic model to gather, compute, report,and operate on digitalized data seamlessly for improvingthe learning methods. EDM as well as LA applied in theeducationfieldreformtheavailabletechniquesofeducation by offering novel solutions to the interactionissue.LMS-LearningManagementSystemisavirtualizededucational platform that bridges the gap between facultyandstudents.Itprovidesvariousmeansthrough whichthefaculty and student can have better communication. Itenablesthefacultytosharematerialsandstudentstoraisequeriesaswellastoclear doubts.
ConcentratedontheapplicationofDManddataanalyticsforhandlingthedataproducedfromtheeducational industry. The EDM and LA methodologieswere defined for managing the big data in commercial aswellasalternatecommunities.Also,itprovidesanextensive definition in EDM and LA which affects thefunction of shareholders in the PG level education center.Moreover, a brief description of applying these models,and examining the learning process of students, assessingthe performance to provide extensive feedback practically.Eventually,thesemodelsaffecttheadministrativeprinciples which are qualified for all stakeholders in aneducationalinstitution.
Alsuwaiket et al. (2021)[5] various data preparationprocess has been deployed with massive student recordsforpreparingthestudentsmarksaccordingtotheassessment modules. Here, data is computed under variousphasesforextractingthecategoricalfactorwherestudent's marks have been refined in the data preparationstate. Consequently, the final marks of students are notisolatedfromtheenrolledmodules.Followedby,the examinationofEDMdatapre-processingphaseshasbeenperformed.Typically,itisfinalizedthateducationalinformationshouldnotbedevelopedsimilarlyasalternatedata types because of the variations like data sources,applications,anderrorsinvolvedinthem.Hence,courseworkestimationratiohasbeenemployedforconsidering various module assessment approaches at thetimeofpreparingstudenttranscriptiondata.Theimpactofcourseworkassessmentratio(CAR)ondetection byapplyingRFclassifierhasalsobeen presented.

FEATURESELECTION

ThemainaimofFSistopickupafeaturesubset fromthe input data to limit the noise and unwanted parametersandexhibitsaneffectiveperformance.The majorapplicationsingenemicroarrayanalysishavebee

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nemployed (Guyon et al., 2019) [6]. The remarkable geneexpression data is composed of massive parameters werehighly associated with alternate variables. The dependentparameters are not effective in providing additional dataregardingclassesandfacilitatedasnoiseforapredictor.Itrefers that overall data content can be attained from someexclusivefeatureswithhigherdifferentiatingdata regardingtheclasses.Therefore,bythereductionofdependent parameters, the volume of data is mitigatedwhichintendstoenhancetheclassificationfunction.Ina few sectors, parameters that are not connected are servedas pure noise that develops a bias in predictor and limitstheclassificationoperation.Itexistswhenthedata isinsufficient previously. Under the application of FS, fewinsightsareobtainedandmaximizetheprocessingdemand aswellaspredictionaccuracy.

PROFILINGANDCLUSTERINGSTUDENTS

Asthenamesuggests,theresponsibilityofthe seapplicationsareprofilingstudentsreliedondiverseparameterslikefeaturesandknowledge.Groupingstudents are performed on the basis of diverse propertiesof profile data.Therefore, it is varied fromclusteringtechnology is varied from one another, since the aim is toclusterthestudents.Additionally,ifthestudentsaregrouped,eachindividualseeksmassivedissimilarityamong clusters; however, it is not feasible in groupingtasks.Atthetimeofdevelopingateaminacourseproject,each member prefers to cluster the students. Likewise, thecategories of applications, various DM approaches areutilizedfortheseapplicationslikeFSandclustering. Unpresentedatechnologytosegmentthelearnerswiththehelp of dissimilarity value using Random Forest (RF);employed sequence mining approaches to find learningbehaviorpatternfordiscriminatingdiversestudentgroups.It applied a process of grouping and profiling the learneraccordingtothecommunicationswithITS. ThepreprocessingmodelofEDMisnamedasClustering. It is defined as unsupervised technology fordetermining data in statistics, ML, pattern analysis, DM,and bioinformatics. It is applied for gathering identicalobjects for cluster development. A cluster is composed ofobjects which are identical to one another; however, it isno identical to the objects of alternate groups. It is usedwhileexaminingthedatasetobtainedfromtheeducationalsystem is named as Educational Data Clustering (EDC).The educational center is categorized into 3 classes asTeacher,Student,andEnvironment.Communicationbetween the 3 actors produces quantifies data which aregroupedsymmetricallyforminingthevaliddata.Therefore,dataclusteringactivatesacademicians forpredicting student function, the associate learning style ofdiverse learner kinds, and the behaviors that enhance theinstitutionalperformance.Authorshaveperformed variousstudiesoneducationaldatasetswithbetterefficiencybasedon academicfunction in examinations.

SYSTEM ANALYSISEXISTINGSYSTEM

Specifically,therearetwomentorsforinnovationeducation students. One is a university teacher, and theother is corporate executive or innovation elite, that is, oncampusandoff-campusmentors.Thecombinationofbasictheoriesinsidetheschoolandsocialpracticeoutsidetheschoolcanenrichtheteachersandoptimizetheteacher structure.Italsotrulyrealizesthedockingofschool-enterprise professional mentors and innovation mentors,the theoretical knowledge and innovation skills. It plays ahuge positive role in cannot improve students' knowledgeand literacy. Existing systems Innovation and educationcoursesmainlyincludethecontentofinnovationknowledge, innovation ability, and innovation awarenessandinnovationqualityverylowandperformancecomplicated. From the perspective of the system, somecourses will appear in the teaching plan of the businessmajor.Forthispartofthecourse,teacherscanbeencouraged to incorporate relevant innovation knowledgeindailyteaching,suchasmarketingcourses andmanagement courses.Some courses canbe offered aselectives,andstudentswithinnovationdesireareencouraged totake such courses.

DISADVANTAGES

- Performancelow
- Students'interactionanalysisverylow.
- Datasettestingdifficult.
- Maintenanceverycomplicatedofthiseducationsystems

III. PROPOSEDSYSTEM

Theimplementationofthedualmentorsysteminschools and enterprises can also facilitate. The effectivehybridizationoflinearvectorquantizationmodelforforeseeingtheeducationalperformanceandemployabilitychances of the students is presented. The working modelof the hybridization of linear vector quantization modelforEDM.Itassiststhefacultiesinidentifyingpoo

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rlearners in education and placement. In this objective, apredictive model using LVQwithrandom forest techniqueis integrated to develop a hybridization of linear vectorquantization algorithm for predicting the employabilitychancesandacademicresultsofthestudents.Thehybridization of linear vector quantization is simulatedusinganeducationaldatasetandthestudents areinvestigated with varying threshold weights on a yearlybasis. It performs prediction by the use of several factorslike regular attendance, internal/ external marks, scoringin placementtrainingprograms,andso on.

ADVANTAGES

- EducationDatamaintenancesimple
- Morethanonedatatestedofhighaccuracy
- Students'interactioniseasy
- Differenttypesoftestingprocess
- Performanceimproved

SYSTEMARCHITECTURE

The model is mainly executed in the pre-processingtask. In this proposed method block diagram is representedin figure.

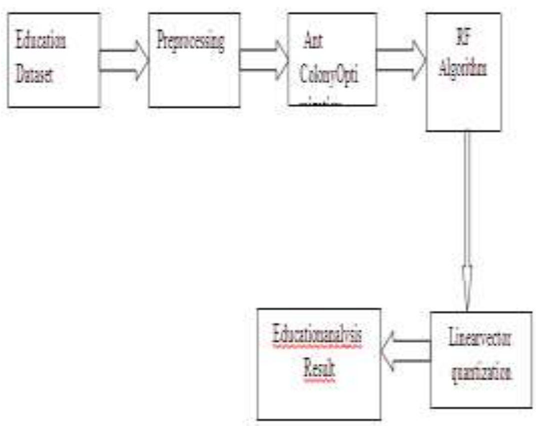

Fig1: System ArchitectureDiagram

In this model is presented as an effective model thathelpscomputetheperformanceofastudent'seducation.Itfindsusefulandessentialforthemtobeplacedinpresumededucationalinstitutionsandreachagoodposition in the future. Then, it is not only a favorablesystem for students, it also useful for the professors forteachingandenhancingtheirskillsandtalentsbycontributing to diverse parts of academics where bothstudents and teachers would empower their knowledge.The main aim of this model is to find the students' learningperformance ineducation anddetect whether they areskilled. The error is measured for every predictive task andvalidateswhetherthevaluesareexactornot.Also,weightsareextendedifthesamplesareclassifiedincorrectly in the upcoming rounds. Secondly, boostedweightisfedasinputtotheLVQapproachtoclassifyanddetect the student's educational activities by means of thepass or fail as well as placement performance in light ofgot placed or not. Finally, a diverse set of models wereemployedonsampledataforcomputingtheclassificationaccuracy of variousapproaches.

MODULE DESCRIPTIONPREPROCESSING

In the ACO-LR model, preprocessing takes place intwostagesnamelyformatconversionanddatatransformation. In the beginning, the format conversionprocess takes place where the data in any other formatssuchas.xlswillbeconvertedinto.csvfiles.Then ,thedatatransformation process will begin where the data presentin diverse formats in the dataset are transformed in anappropriately.

ACOBASEDFEATURESELECTION

Here, ACO-FS is executed to pick up the feature subsetfrom the educational data. ACO is a population-basedmetaheuristicalgorithmwhichhasthecapability ofsearchingthepopulationinparallel.Itoffersafasterexplorationoftheoptimalsolutionandadaptstomodificationslikenewdistance.Besides,theACOalgorithm has offered a better convergence rate. So, it isappliedfortheselectionoffeaturesintheappliededucationaldata.TheintentionofFSforACOistorecognizetheminimumfeaturecountandtoattainmaximumclassifieraccuracywiththereducedprocessingexpense.

EDMisanactiveresearchareaandtheDMtechniquesare used for the extraction of useful knowledge on thecharacteristics of the students in the learning process. InEDM, the FS process is mandatory for the generation ofthe subset of candidate parameters. As the FS task acts asamajorpartoftheclassificationresults,itbecomesessentialtodeterminethe effectivenessofthe studentassessment methodology with the FS techniques. In thiswork, ACO algorithm is utilized as a feature selector tochooseanoptimal set offeatures.

The ant is presently at node i and has an option ofwhichfeaturestoincludesubsequenttoitsroute.Itselectsafeature$j$ nextusingthetransitionrule,followedby$k$and l.Uponarrivalat$l$,thepresentsubset$\{i,,k,l\}$is

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computedforfulfillingthetraversalterminationcriteria .Theantgetsterminated its traversal and provides the feature.Properheuristicdesirabilityfortraversalisappl iedbetweenfeatureswhicharesubsetevaluationfuncti

ofantk atfeatureidecidedtotraveltowardsthefeature$j$ attime t:

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}(t)]^{\beta}}{\sum_{l\epsilon J_i^k}[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}(t)]^{\beta}} & j\epsilon J_i^k \\ 0 & otherwise \end{cases}$$

Where,ηijdenotestheheuristicdesirabilityofdeciding a feature $j$if at feature $i\eta ij$is nonobligatoryexcludingoftenhigheralgorithmicoutc omes,Jikrepresents the set of neighboring nodes of node i which isunvisited by an ant k. $\alpha > 0$, $\beta > 0$ are 2 attributes thatproceed the equal importance of pheromone value as wellasheuristicdataand(t)referstheamountofvirtualp heromoneonedge (i,).

RFBASEDCLASSIFICATION

Finally, the RF classifier gets executed to classify thefeaturereduceddatatoidentifytheclasslabelinanap propriate way. The classification models mainly

ons.Theheuristicdesirabilityoftraversal,aswellasedg epheromonelevels,arecombinedforproducingprobab ilistictransitionrule,whichindicatestheviability

usedfor developing an approach for mapping the data to aspecificclassbymeansofexistingdata.Itisemployedf or extractingrequireddataitemsfromthismethodfordete ctingadatamovement.ThedependentattributeoftheR F scheme is a binary-classification. to find an optimalsubset,havingaccuracycomparablebutsizem uchsmallerthantheoriginalRandomForest.Weshowt hattheproblem of selection of optimal subset of Random Forestfollowsthe dynamicprogrammingparadigm.

Let us assume, we have a Random Forest containingfour elements namely T1, T2, T3 and T4. Now to chooseanoptimalsubsetoutofthisforest,someelement shavetobe removed. Consider figure 5.4, in which one tree of theforestiseliminatedin eachiteration.Thecostofcomputingaccuracyofthesub setobtainedafterremovingtrees T1 then T2 is the same as that obtained by firstremoving T2 and then T1. In this process of finding theoptimalsubset,manysubsetsofRandomForestre-appear.

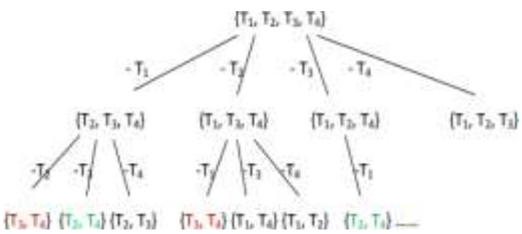

Fig2: DynamicTreeImplementation

We store the accuracy for each of the distinct subsetsand later when the subsets reappear, values can be simplylooked up. In this way problem of finding optimal subsetofRandomForesthasbeenmodelledusingDyna micProgramming.AscanbeseenfromtheFig-2,ateachstage the number of unique subsets obtained by removing treescanbeexpressedasNCKwhereKisthesizeofsubs etsatthat stage. Thus, total number of distinct subsets can beshown as,

$$\sum_{k=1}^{N-1}\binom{n}{k} = 2^N \text{-}1$$

Using the formula for binomial expansion. A closelookattheexpressionrevealsthatwehaveinfacten umerated Power-Set of size N (2N). The two subsetsleft out are the empty set, which is of no use, and thecompleteset,whichrepresentstheoriginalRandom Forest.

IV. RESULTS AND DISCUSSION

One by automatic program code andotherbyprogrammer'smanuallywrittencode.Aco degeneratorisasuiteofprogramsthatmatchestheinputt oanappropriatecodetemplateandfromtheseproduces' modulesofcode.Thecodeismadesimpleinsuchaway

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that another programmer can easily understand and workonthatinfuture.Thecrucialphaseinthesystemdevelopmentlifecycleisthesuccessfulimplementationof the new system design. The process of converting as newor revised system into an operational one is known assystem implementation.

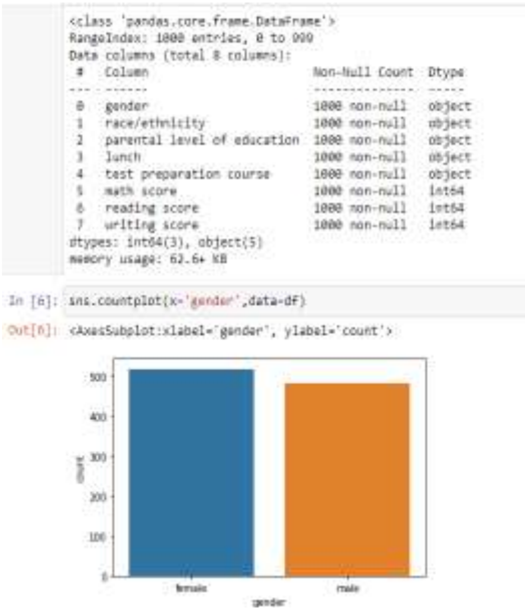

Fig3:GenderWiseComparisionAnalysis

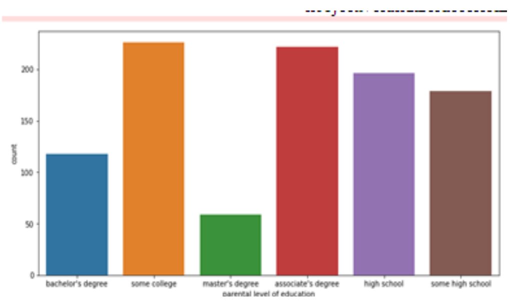

Fig4:DegreeWiseComparisonAnalysis

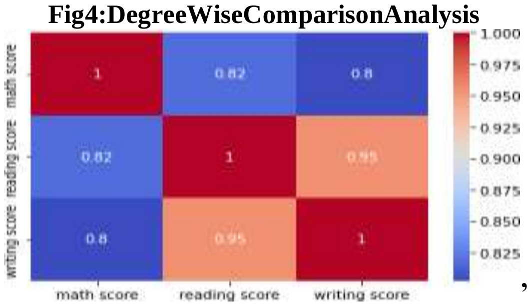

Fig5: ScoreWiseAnalysis

V. CONCLUSION

This work has concentrated on the design of effectiveDMmodelstoexaminetheeducationalperformancelevelto assist students as well as faculties to improve theirperformancetothenextstage.Theproposedresearchwork has incorporated a set of three processes namelypreprocessing,featureextraction,andclassification.Theseresearchworksinvolveasetofthreeresearchobjectivesandaresuccessfullydeveloped.Novelhybridizationoflinearvectorquantizationmodelispresentedforpredictingtheacademicperformancesand hybridization of linear vector quantization algorithm forpredictingtheemployabilitychancesandacademicresultsofthestudents.Theproposedhybridizationoflinearvectorquantizationmodelassiststoexaminetheacademicstudent'sperformanceandalsopredictedwhether thestudentgetsplacementinaprestigiouscompanyforachievingthegoals.Theexperimentalresultstatesthatthehybridization of linear vector quantization model offersthe forecast that has 90% precision comparatively greaterthan RF. employabilitychancesofthelearners.Inthisobjective, predictivemodelusingRFisintegratedtodevelopa

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