IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 07, 2022

A Novel Approach for E-Commerce System for Sale Prediction with De noised Auto Encoder and SVM Based Approach

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***Abstract*–E-commerce,oronlineshopping,hasgrownin prominenceoverthepastfewyearsthankstotheproliferation oftheInternet.Yet,therearealotofthingsthatcanaffectan online store's success, and if the operators don't correctly assess their supply and marketing partnerships, they could lose a lot of money. Thus, it is crucial to create a model that can reliably produce high precision sales prediction in order toguaranteethelong-termsuccessofe-commercebusinesses. Thesuggestedmethodcomprisesthreestages:preprocessing, Feature selection, and model training. This work uses zero-phase component analysis and normalization in the preprocessing phase to get rid of noise and inconsistent data. Finally, the model is trained with DAE-SVM after information gain is employed for feature selection. When compared to convolutional neural network and support vector machine models, the proposed model excels.**

***Keywords*— E-Commerce, Sales Prediction, Denoising Auto Encoder (DAE), Information Gain (IG).**

I. INTRODUCTION

E-commerceplatformscollectalotofdata,whichisstored securely in their data centers. If they don't put this informationtogooduse,they'llloseoutonalotofmoney. Information such as a customer's searches, registration data,chatlogs,andpurchasehistoryisbeingstoredintheir server and will only be accessed in the event of a data breach.Theemphasisoftheresearchisononlineshopping. Acompany'sculturecanshiftforthebetterorfortheworse as a result of adopting a new approach to data collecting andanalysis.Theymaybereluctanttosharetheirdatawith an outside organization for fear of violating their privacy, buttheymightinsteadhireateamtoundertaketheanalysis in-houseandpocketthesavings.Inrecentyears,China'se-commerce industry has expanded rapidly, with most transactions taking place online. Thanks to the efforts of JingdongMall,AliGroupandothercompaniestoimprove thebasicplatformconstruction,thegrowthofe-commerce in our country has entered the stage of rapid development ofsmallandmedium-sizede-commerceenterprisesrelying on platform strength to compete and develop their own uniquecompetitiveness.Smallandmediumsizede-commerce enterprises can launch tailored goods and servicestobettermeettheneedsoftheircustomers,aswell as to achieve market segmentation and service optimization. Yet, due to constraints in technology and resources,smallandmediume-commerceenterpriseshave notpaidenoughattentiontothevastamountsoftransaction dataresourcestheyget[1].Hence,internetproductreviews can sway purchasers because they are typically telling of the product's quality. Reviews for Product A that are featured on product detail pages talk about the sellers' exaggeratedclaimsabouttheproduct,helpingthecustomer make a better educated purchase decision. Meanwhile, e-meteoric commerce's rise and rising popularity have contributed to a rise in sales volume. Furthermore, sales forecasting plays an important role in both traditional and onlineretailbysignificantlyinfluencingstock-keepingand marketing strategies. E-commerce businesses and academics alike have shown a growing interest in sales forecastinginrecentyears.Therearenumerousapproaches suggested for forecasting sales. For sales forecasting, the tried-and-true univariate time series model has been recommended.Thisproposedusingfuzzyneuralnetworks to forecast sales. A sales forecasting system using a fuzzy neuralnetworkandstartingweightsproducedbyagenetic algorithm was proposed by proposed a hybrid extreme learning machine and classic statistical model for sales forecasting.Ithasoutlinedafewissuesthatonlineretailers face, including customers' concerns about their personal informationbeingmisusedandtheawkwardnessofmaking apurchasewithoutfirsthandlingtheitem.Noteverybuyer will find your website interesting because of the content. Differentclientshavediversepreferenceswhenitcomesto apparel, for example. The same holds true for a web host who promotes particular goods on their site. Coming up with the proper results according to the customer's choice is a time-consuming process. A company's ability to enter new markets and increase revenue is greatly enhanced by accurate projections. Budgeting is based on accurate cost estimatesandrevenueprojections,bothofwhichcanbe considerably improved with the use of data mining. A company'smarketing,operations,finance,production,and sales departments, among others, rely heavily on accurate sales forecasts. To attract investment capital and optimize internalresources,businessesmusthaveaccesstoaccurate and reliable sales forecasts. This proposed approach to takes a novel approach by focusing on the most effective strategies for forecasting future sales.

II. LITERATURESURVEY

E-commerce platforms have designed and developed a wide range of artifacts, such as easy checkout process, quick product search, user-friendly design and convenient and ubiquitous access through various web and mobile platforms[2],toencourageafavorablepurchasedecisionat each and every customer interaction. A web interface's levelofinteractionhasbeenshowninmultiplestudies[3]to have a substantial impact on whether or not a shopper completesatransactiononacertainshoppingplatform.As makingapurchaseontheinternetisdifferentfrommaking a purchase in a physical store, the platform also plays a significant role in the final choice to buy. These results have prompted a number of studies investigating the influence of persuasive design on digital platforms [4]. Research in the social and medical sciences focuses on a number of important questions, including how to predict influenzaepidemicsandhowtogetthepublicinterestedin theseissues.Afterseeingasubstantialassociationbetween the relative frequency of certain questions and the number of patients with influenza, [5]constructs a model for influenzasurveillanceusingGooglequerydata.Byadding a calendar to the simple linear model, [6]creates a time series model; by adding Google query data, he creates a mixed model. As a result, this proposed can make more precisepredictions.Thebenefitsanddrawbacksofutilizing Google search data to predict influenza are examined by [7].Theydemonstratethevalidity,stability,andtimeliness gainsfromleveragingsearchdatatoestablishanepidemic surveillance system. To determine how much people care about issues like terrorism, climate change, and access to healthcare. Information gleaned via web searches is the subject of[8]. In today's data mining world, decision trees (DT)arecommonlyused.Itiscommonpracticetoemploy information extraction for purposes such as classification and prediction [9] Since it is insensitive to the size and dispersion of the underlying data Decision trees (DT) are hierarchical data structures in which choices are made at each node. Existing issues, system construction, rural logistics modes, and other issues are the main concerns of China'sacademiccommunity.Forinstance[10]describeda coordinated operation mode of rural logistics based on industry chain integration, common logistics, and supply chain integration, with rural e-commerce in Hunan Province as the research topic. From the vantage point of supply-side reform, analyzed the current state of rural logistics in China. The authors [11]investigated how the developmentofhighwaysimprovedtheefficiencyofrural logistics companies. Thephrase "farmdigitallogistics"was first used in the context of the German market by [12]Traditional farm logistics were compared to agriculturaldigitallogistics,anddataownershipand privacy problems were also discussed [12]. A successful business model is the outcome of a successful marketing strategy, say [13]. The simplest and most effective way to put this plan into action is to encourage customers to bargainforalowerprice.Asbuyers aregiven thefreedom to determine the selling price, "name your own price" (NYOP) has become the standard pricing structure. Most vendors would consider recent and past deals that went smoothly before opting to cut prices. When a certain number of a product are sold during a certain time period, thepriceisreduced.Aclearancesaleisanotherstrategyfor luring buyers than simply lowering prices. Large markdowns on unsold stock are a standard retail practice. Buyers may have passed on the item because they thought theaskingpricewastooexpensive,ortheymayhavefound a comparable product somewhere that better met their needs. Hence, prices will fall to match or even fall below sellers' expenses. Most retailers will have already calculated the loss on an item before slashing prices significantly [14]. Predicting how many of a certain product will sell is a significant and challenging subject in online retail and marketing. If stores knew how products were selling in advance, they could more effectively manage inventory. E-commerce platforms could also benefit from this insight by making more informed recommendations to clients. This is especially true for time-sensitive sales events, also known as "flash sales" [15], which try to rapidly liquidate inventory. Cold start problem [16] refers to the challenge of giving suggestions toconsumersintheabsenceofanypriortransaction.Toget around this, it is usual practice to use existing contextual information linked with the item or the user. [17]used a modular neural network to anticipate Tokyo Stock Exchange stock prices, and the system was successful in a simulatedtradingenvironment,yieldingagoodreturn.[18] used a neural network model to accurately anticipate market fluctuations. Gold price variations were simulated and predicted using artificial neural network modeling by[19],andtheirRMSEandMAEwerecomparedtothose of the ARIMA model. The findings proved that the ANN model yielded more precise forecasts [19]. Using a BP neural network model,[20]forecasted the Chinese steel price index with a relative error of 0.315% between 2011 and 2013. This experiment shows that the BP network is superior in its ability to anticipate outcomes. Machine-learning algorithms are helpful for dealing with non-linearityinempiricaltimeseriessincetheyaredata-driven andneedlittleapriorіassertionsaboutthedata-generating process[21]. Due to this fundamental property, machine-learning methods, such as artificial neural networks (ANNs),havesurpassedothermethodsasthegoldstandard for simulating real-world events[22]. To account for data-specific aspects including trend, autocorrelation, exogenous variables, and seasonality, forecasting models are often selected manually in practice and research[23]. Because of this, there have been contradictory findings on the effectiveness of statistical methods against the effectiveness of machine-learning methods for modeling andpredictingretailsales.Thisproposalcontributestothe existing literature by offering new, well-supported conclusionsbasedonthemostrecent available information. Thefinalsetofworksexaminesthefactorsthatinfluence

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consumers' purchasing intentions through surveys, with a focusonpurchaseprediction.Onesuchstudywas undertakenby[24],whosurveyedcustomerstodetermine theimpactofvariousfeaturesontheirpropensitytobuy jewelry,apparelandaccessories.Beinginspiredbythe aboveresearcharticletheproposedapproachusesDAE-SVM totrainthe model.

III. PROPOSEDSYSTEM

Preprocessing,FeatureSelection,andModelTrainingare thethreestagesthatmakeuptheproposedmethod.Throughtheprocessoffeatureextraction,theoriginal feature space is shrunk and replaced with a new one. The new,smallerspacekeepsalltheoriginalcomponentswhile replacingthemwithamoremanageablesubset.Inputdata ischangedintoasimplifiedversionoftheoriginalfeatures when the number of features is too large to handle in its current form. Just the selected features are used in the classifier's training and assessment processes during feature selection.

A.Preprocessing

In light of the fact that the crawling original data is prone to noise, incompleteness, and inconsistency, this paper normalizes and zero-phase components the data before running the experiment.

1)Normalization:

To lessen the impact of data polarization on the final prediction results, as demonstrated by the following formula,normalizationshouldbeperformedasapartofthe preprocessing phase for experimental data [25].

$$Z_m = \frac{X_m}{y} \tag{1}$$

where Y is the total number of samples, $Z_m$denotes the weight of an attribute's total parameters over all samples, and$Y_m$denotesafeaturevectorforasinglesamplewith$m$ attributes.

2) ZeroPhaseComponent Analysis

Normalized data should undergo zero-phase component analysis. It takes P randomly chosen samples from the source data to create the matrix$Z_1 = W_1$. ZCA whitening processing on the dataset with a single sample dimension of 8 The following demonstrates the particular procedure:

Infirststep,makeZ^S_1anumericmatrixcontainingthe initial $8*p$ofdata.Fisthematrixthatresultsfrom normalizing,$Z^S_1$and the average of its F attributes is 0. In secondstep,Samplecovariancematrix$\sum F$canbe calculatedtoobtaintheeigenvaluesandeigenvectors;then, theycanberankedfromlargesttosmallest.$\mu_1,\mu_2,...\mu_8$is the set of all eigenvectors, and the corresponding eigenvalues are labeled $V=[v_1, v_2, \cdots, v_8]$

Therotationmatrixisobtainedbymultiplying$V^T$by U^T_1

$$W^{Sg}_{1rot} = V^S W^S_1 = \begin{bmatrix} v^s_1 z_1 & \cdots & v^S_1 z_p \\ \vdots & \ddots & \vdots \\ v^S_8 z_1 & \cdots & v^S_8 z_p \end{bmatrix} \tag{2}$$

Createuniformlydistributedvaluesfortheattributesofthe rotation matrix:

$$W^{S_g}_{1rot} = \frac{1}{\sqrt{\mu_1} + 0.1} W^S_{1rot} \tag{3}$$

Tocalculatetheunitvarianceperattributeintherotation matrix,wemultiply$\frac{1}{\sqrt{\mu_k}}$(k=1,2,...,8)byeachelementof rowk(k=1,2,...,8)in W'_{1rot} andcalltheresultingmatrix $W''_{1rot}$where $1/\sqrt{\mu_k} + \varphi$+replaces$\frac{1}{\sqrt{\mu_k}}$,whichaddresses numericalfluctuationsoroverflowsas$r_k$approaches0. The following are the outcomes of ZCA bleaching:

$$Z^s_1 = V Z^s_{1rot} \tag{4}$$

B.FeatureSelection

In the fields of machine learning and data mining, feature selection has been a hotspot for investigation. The aim of feature selection is to narrow down the number of input variables by omitting those that provide little to no predictive value. The dimensionality of feature space is reduced by feature selection by eliminating superfluous, unnecessary, or noisy information. Immediate benefits for applications include faster algorithms, higher quality data, and better classification accuracy [26]. Information Gain (IG) based feature selection, a prominent filter model, is used in our study toaddress the computational complexity of ensemble approaches and the increased computational burden of wrapper model.

1) InformationGain

EntropyhasavitalroleinthedefinitionofIG.Entropy isapopularmetricininformationtheorythatdescribesthe qualityofanygivensetofsamples.TheIG-basedfeature selectionreliesonthis.Thedegreeofrandomnessina systemcanbequantifiedbylookingatitsentropy.For$X$ is entropy, we have:

$$(X) = -\sum_{x \in X} (x) log_2 (r(x)) \tag{5}$$

Tobemoreprecise,let'ssaythatYhasamarginal probability density function of $r(x)$. A relationship between features X and Z exists if, after partitioning the observedvaluesofXinthetrainingdatasetUaccordingto the values of a second feature Z, the entropy of Z with respect to the partitions generated by Z is less than the entropy of X before partitioning. Then, after seeing Z, the entropy of X is:

$$E\left(\frac{X}{Z}\right) = -\sum_{z \in Z} r(z) \sum_{x \in X} r\left(\frac{x}{z}\right)_2 \left(r\left(\frac{x}{z}\right)\right) \tag{6}$$

Theconditionalprobabilityof$x$givenzisdenotedby $r\left(\frac{x}{z}\right)$.Itmaydevelopametricthatreflectstheadditional informationabout$X$providedby$Z$,whichindicatesthe amountbywhichtheentropyof$Z$reduces,usingentropy as a criterion of impurity in a training data set U. IG is the name for this metric. It's a result of:

$$IG = E(X) - E\left(\frac{X}{Z}\right) = H(Z) - H\left(\frac{Z}{X}\right) \tag{7}$$

ISSN PRINT 2319 1775 Online 2320 7876
Research Paper, UGC CARE Listed (Group -I) Journal Volume 11, Iss 07, 2022

For proof, see Eq. (7); IG is a symmetric quantity. Observing Z provides the same amount of information about X as does the other way around.

C.Trainingthe Model:

1) AE

When modeling high-dimensionaldatainan unsupervised setting, AE is an effective tool. The system includes an encoder, which converts the input data into a compressed code, and a decoder, which can read that code and reconstruct the original data. The encoding acts as a bottleneck for information, compelling the network to focus on extracting common patterns from high-dimensional data.

Equations(8)and(9)showthatAEisa neural network methodwiththeoperationallogicoftrainingtheinput vector to be reconstructed as the output vector using unsupervised methods. In these equations, ω is the nonlineartransformationfunction,$_1$,$c_2$andt_1,$t_2$arethe biasandweightoftheneuralnetwork,andisthenonlinear transformation.

$$x=h(z)=\omega(T_1z+c_1) \quad (8)$$
$$b = (z) = (T_2z + c_2) \quad (9)$$

The encoder compresses the data to extract the values that bestrepresentthefeaturesoftheinputdata;thedecoder networkreconstructstheinputdatafromthesevalues.The encoder is used to conduct a nonlinear mapping from the input layer to the hidden layer. The encoder applies a transformation to the hidden layer, while the decoder restores the original input space.The difference between the input vector and the reconstructed vector is the reconstructionerrorr.IntheAE,thereconstructionerroris kept as small as possible by an unsupervised training procedure.In thisstudy, we employ theequation where$M$ isthenumberofobservationsandeistherootmeansquare error.

$$q=||b-z||\sqrt{\frac{1}{m}\sum_{k=1}^{M}(b-z)^2} \quad (10)$$

The AEmodel'sabilitytodetectanomaliesisimpactedby thethresholdyouchoose.Inthisarticle,themodel'scutoff valueisdeterminedusingthekerneldensityestimation

(KDE) technique [27]. Estimating the likelihood of a randomvariableusingKDEisanonparametric approach.Theshapeofthedistributionfunctionofthe variables under examination should not be assumed. Compared to relying on subjective judgment to establish thresholds, this approach is more objective and rational. The Kernel Density Approximation of the Critical Value

$$\beta=\frac{1}{me}\sum_{k=1}^{m}F(\frac{q-q^{(k)}}{e}) \quad (11)$$

where(.)istheGaussiankernelfunction,hthe estimatedparameter, e>0and$m$thenumberofsamples forwhichhisgreaterthanzero.DAEintroducesnoiseinto the raw data in order to prevent the phenomenon of overfittingtheAEduringprocessing.Then,faultydatacan be encoded and decoded to increase the model's relative robustness.

The original data are transformed into data contaminated by noise before being used as input for encoding and decoding. Here is how DAE is encoded and decoded:

$$x'=h(\tilde{z})=\omega(t_1\tilde{z}+c_1) \quad (12)$$
$$y'=(x)=\omega(t_2z+c_2) \quad (13)$$

So,thefollowingistheinaccuracyinitsreconstruction:

$$q=||f_\theta(h_\theta(\tilde{z}))-z||=\sqrt{\frac{1}{M}\sum_{i=1}^{M}(f_\theta(h_\theta(\tilde{z}))} \quad (14)$$

2) SVM

Statistical value machine learning, or SVM, is one such technique. The training time, training sample size, and classificationaccuracyareallsignificantlyimproved.Fast, rapid, and accurate fault diagnosis is crucial for complicatedproductionequipmentlikeESPs.SVMiseasy to implement and does not necessitate a huge amount of dataincomparisontootherclassificationlearningmethods.

Maximum intervals are crucial to how support vector machines classify data. The samples are divided using a hyperplane. The equation of the separation hyperplane for thesampledataset$S$={(z_1,x_2),...(z_p,x_p)},where$z_k \in R^A$isthesampleeigenvector, x_k= {−1,+1},and i = (1,2, ... n) is as follows.

$$\vartheta^s z_k+C=0 \quad (15)$$

Whereas C vector and represents a weight vector. The maximum intervalseparationhyperplaneanda categorical decision function can be used to transform a constrained optimization problem into the following optimization issue:

$$\begin{cases} \frac{1}{2}||\vartheta||^2+D\sum_{k=1}^{m}, \\ (\vartheta^s z_k+C)\geq 1-\epsilon_k, \\ s.t\{ \quad \epsilon_k\geq 0, \\ \quad k=1,2,\ldots n \end{cases} \quad (16)$$

Thepenaltyerrorinclassificationisdenotedbythepenalty factor D. If it's too big, the classifier won't be able to generalizewellbecauseofallthehyperplanelimitations.If it's too tiny, the classifier might not do a good job of distinguishingbetweensimilarinstances.Theevalueyou select shouldbe contextual.Misclassificationsin alimited number of samples are tolerated because they have little effectonthewhole.Lackvariables$\epsilon_k$areintroducedto simplifythecriteriaforimplementingthemodel.The intervalmaximizationproblemisobtainedbythe

LaGrange function introduction and the radial basis function (RBF) $(z_k,)$ kernel function of the inner product algorithm.

$$\begin{cases} (z_k,z_i)=\exp(-\alpha||z_k-z_i||)^2 \\ ()_{o\beta}=\sum_{k=1}^{n}\beta_k-\frac{1}{2}(\sum_{k=1}^{n}\sum_{i=1}^{n}\beta_k\beta_i(z_k,z_i)) \\ s\sum_{k=1}^{n}\beta_k x_k=0,0\leq\beta_k\leq D \end{cases} \quad (17)$$

The argument α in the kernel function. The LaGrange multipliers of $x_k$and $x_i$are denoted by $\beta_k$and , respectively.As a result, the following expressions reveal the SVM's optimal classification function:

$$h(z)=(sgn\sum_{k=1}^{p}\beta_k x_k L(z_k,z_i)+C) \quad (18)$$

In conclusion, the major parameters that determine SVM performance are the penalty factor D and the kernel function parameters α.

IV. RESULTANDDISCUSSION

All assessment matrices employed by the researchers' algorithms will be displayed alongside their respective results and discussions. The study's focus on sales forecasting necessitated the employment of three regressionmodels:SVM,CNN,andDAE-SVM.Thereare numerous assessment matrices that can be used to assess the quality of a regression model. The researcher plans to evaluate the models using the Accuracy and RMSE metrics.Eachmodel'soutputwillbecomparedtotheothers to determine whether one is more accurate.

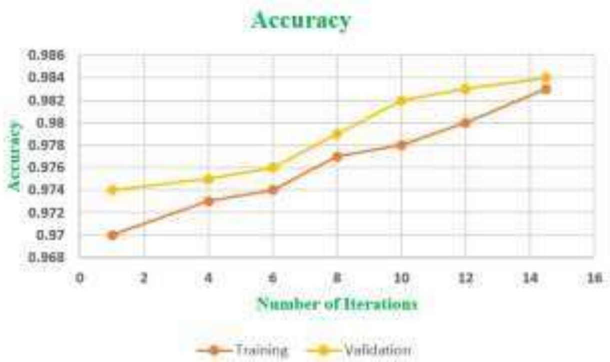

Fig.1.AccuracyComparisionoftheDAE-SVM

In Figure 1, we see how training acc and validation acc correspond to the accuracy of the training set and the validation set, respectively, as a function of the number of iterations.

Fig.2.LossofDAE-SVMModel

By comparing the two picture curves shown in Figures 1 and 2,we cansee thattheaccuracyof boththe training set and the validation set improves with time. During period 14, the model is considered to have converged to the optimalstatesincetestingandverificationaccuracytendto stabilize at a maximum of 0.984 and the loss curve gradually diminishes.

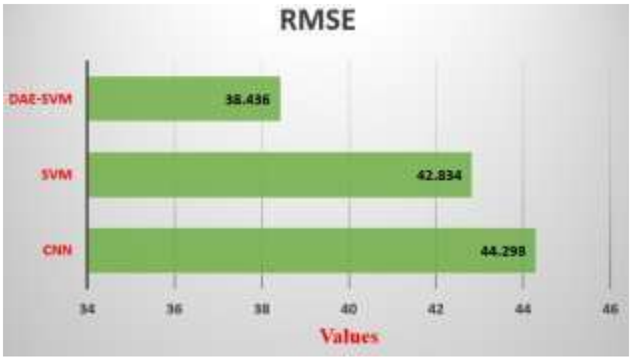

Fig.3.RMSEofDAE-SVM Model

DAE-SVMwasshowntohavethebestperformanceofthe three approaches. With an RMSE of 38.436 (the lowest of thethreesalespredictionmodels),thismodelperformsbest in terms of sales prediction accuracy which is shown in Figure 3.

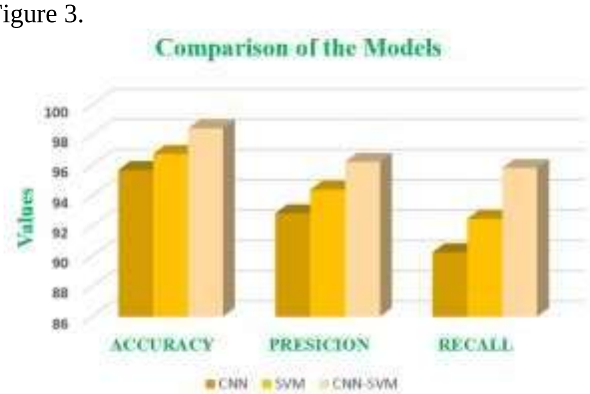

Fig.4.PerformanceEvaluationoftheModels

As compared to CNN (95.69% accuracy), SVM (96.75% accuracy), and DAE-SVM (98.44%), the suggested DAE-SVM based E-commerce sales prediction approachperformsthebestasshowninFigure4.The

ISSN PRINT 2319 1775 Online 2320 7876
, UGC CARE Listed (Group -I) Journal Volume 11, Iss 07, 2022

suggested DAE-SVM based prediction of E-Commerce sales strategy has been validated by a number of analyses.

V. CONCLUSION

Machinelearninghasbecomeanimportantfactorinmany real-worldcontextsandisrevolutionizingevery industry.Education, medicine, and commerceare just a few of the many industries that have benefited from Machine Learning's groundbreaking applications. Companiesarestrugglingtokeepupwiththefast-moving, competitivemarketthanksinlargeparttothefactthattheir sales and marketing efforts have traditionally been conducted without any knowledge of how their customers actually shop. Machine learning has led to profound changes in the field of marketing and advertising.As a result of these developments, the sales team is better able toevaluatecrucialfactorsincludingconsumers'purchasing behaviors, target audience, and sales projections for the comingyears.Thefocusofthisresearchwasondeveloping deep learning algorithms that can accurately predict e-commerce platform sales. when an image is provided as input, Preprocessing is performed to get rid of the background noise. Finally, the features extracted with IG areusedtotrainthemodelwithDAE-SVM.Thesuggested method achieves an accuracy of roughly 98.4%, which is higher than that of the CNN and SVM models.

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