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Research Article

Machine Learning Algorithms for Enhancing Predictive Analytics in ERP-Enabled Online Retail Platform

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ABSTRACT

Enterprise Resource Planning (ERP) systems are known to be key to online retail management and its resources and operations where proper demand forecasting and sales projections are needed to be effective and competitive. This paper presents a Convolutional Neural Network (CNN) based prediction model for online retail systems that are ERP-enabled. Online Retail II is used to test the model. The methodology starts with the large-scale data preprocessing that involve cleaning, feature engineering, label encoding, and normalization with the help of Standard Scaler and then the further division into testing and training sets entails. The following methods are used to evaluate and train convolutional neural network (CNN) models: root-mean-squared error (RMSE), R2-score, mean absolute percentage error (MAPE), and mean absolute error (MAE). With an R2 of 94, MAE of 2.277, RMSE of 2.814, and MAPE of 13.72%, the experimental findings show that the suggested CNN outperforms the conventional machine learning models. Additional comparative analysis indicates the superiority of the CNN over the models of Decision Tree, Gradient Boosting and Random Forest, which prove its strength in reflecting complex transaction patterns. The results highlight the opportunities of deep learning in enhancing online retail forecasting using ERP which, in turn, enhances business decision-making, operational effectiveness, and customer satisfaction.

Keywords: *Predictive Analytics, ERP, Retail Analytics, Machine Learning, Automation, Optimization, Predictive Analytics, Business Intelligence, Sales.*

INTRODUCTION

Nowadays, few businesses can function without Enterprise Resource Planning (ERP) software to help them manage their resources effectively. They lay the groundwork for the administration and integration of critical company operations, such as finance, human resources, supply chain management, and customer relationship management [1]. Over the past few years, online retail platforms have become more and more attractive to ERP systems to help consolidate data, optimize business processes, and gain operational efficiency[2]. As the online business is expanding, companies are relying on ERP-supported environments to coordinate the intricate balance between market needs, supply chains, and resource distribution.

The proliferation of mobile devices, the relative simplicity of online shopping, and the sheer range of products available for purchase have all contributed to the explosive expansion of e-commerce [3][4]. Due to the rise of online shopping, businesses are increasingly relying on data analytics to make decisions. Using information based on ERP integration, businesses are in-place to streamline websites, customize customer experiences, and modify marketing strategies on-demand [5][6]. Consumer behaviour, preferences, and patterns of purchasing can be analysed and offer useful information that enables the business to keep abreast of its competition in the dynamic online retailing environment [7].

The inherently complex systems underlying modern enterprises further highlight the need for predictive analytics. In domains such as manufacturing, energy, and

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transportation, multiple interacting components exhibit non-linear dynamics and emergent properties[8][9]. Online stores, which are part of global supply chains and financial markets, are similarly subject to unpredictable fluctuations due to consumer demand, logistical constraints and market volatility [10][11]. Complex analytical tools such as system dynamics, agent-based modelling, and network theory are required to capture interdependencies and provide optimal solutions to these challenges.

The integration of ML algorithms and ERP systems has revolutionary prospects of improving predictive analytics. ML models have the ability to process large-scale datasets produced by ERP to reveal the unused patterns, demand, inventory optimization, as well as to allocate the resources dynamically [12][13]. By embedding Artificial Intelligence (AI) and ML-driven automation, ERP-enabled online retail platforms achieve intelligent decision-making, improved scalability, and enhanced competitiveness[14]. A paradigm change that helps organizations thrive in the increasingly sophisticated global marketplace is marked by predictive analytics, that allow them to integrate data in real-time and make strategic decisions based on that data.

Motivation and Contribution

With the rapid expansion of e-commerce, online retail platforms generate massive volumes of complex, high-dimensional transactional data that must be effectively utilized for demand forecasting and decision-making. Traditional ML models often fail to capture the complex nonlinear dependencies within ERP-integrated retail systems, leading to suboptimal predictions, wrong inventory management, and poor customer satisfaction. There is an immediate need for sophisticated predictive models that can process massive amounts of ERP data, identify relevant trends, and make reliable predictions to improve operational efficiency and company competitiveness in order to meet these challenges. Motivated by this gap, the present study explores the integration of DL methods with ERP-based online retail prediction to improve forecasting accuracy and support real-time, data-driven decision-making. This research offers several key contributions as listed below:

- Used the well-known Online Retail II dataset for ERP-enabled research; the dataset contains two years' worth of transaction data from an online retailer in the UK.
- Performed extensive data preparation including cleaning, feature engineering (revenue creation, cancellation isolation), handling missing values and outliers, label encoding, and normalization using StandardAero to ensure robust input quality.
- Proposed a CNN architecture adapted for structured transactional data to capture hidden patterns and non-linear relationships for ERP-based retail forecasting.
- developed a retail-specific supervised DL, CNN model that can discern intricate, non-linear trends in purchase data.
- Compared the CNN's predictive accuracy to that of baseline models (Decision Tree, Gradient Boosting, and Random Forest) and evaluated its performance using different error metrics (MAPE, RMSE, R^3-score, and MAE).

Organization of the Paper

This paper is organized in the following way The study is organized as follows: Section II provides a literature review on improving ERP for online retail prediction; Section III details the dataset, preprocessing methods, and model implementation; Section IV presents the experimental results and a comparison of them; and Section V summarizes the important findings and suggests future research directions.

Literature Review

A thorough review and analysis of significant research studies on enhanced ERP-based online retail prediction was carried out to guide and strengthen the development of this study.

Niu (2020) introduces the XGBoost, a model for predicting sales problems at Walmart that combines the XGBoost algorithm with meticulous feature engineering processing. The method presented in this research is able to efficiently mine properties across multiple dimensions, allowing for accurate prediction. Using data from Walmart stores and the Kaggle competition, this study assesses the XGBoost sales forecast model. Results from experiments demonstrate that this method outperforms competing machine learning strategies. This study's RMSSE metric is half as low as the Logistic regression algorithm's and a third of the way down the Ridge algorithm's. Additionally, this article investigates the ordering of features' relevance and derives some helpful recommendations [15].

Alojail and Bhatia (2020) proposed a novel ensemble-based framework for behavioural analytics in e-commerce using ERP-driven data streams, where user sales and search behaviours were classified into "hot" and "cold" buyers. To achieve this, the authors implemented an Ensemble-Blending based Ensemble (EBE) model that integrated bagging, boosting, stacking, gradient boosting machines (GBM), and random forests, assigning higher weights to the most accurate base models. Performance was evaluated across standard UCI datasets. Specifically, with ERP-driven behavioural data, the model reached an overall classification accuracy of 76%, with low RMSE and improved R^2 values, confirming its robustness in handling ERP data streams for predictive and targeted advertising applications [16].

Alojail and Bhatia (2020) Enterprise resource planning systems display material based on the target audience. For commercial or online behavioural advertising purposes, this study provides a comprehensive analysis of user behaviour. The fundamental objective of this article is to classify and efficiently conduct targeted advertising using data that shows users' purchasing behaviour. Data driven by ERP systems gives rise to behavioural analytics in this context. Along with this, highlight a number of data streaming technologies that aid in the creation of a pipeline for the massive amounts of data stored in the ERP system's database [16].

Ji et al. (2019) Studies on machine learning for predictive analytics in ERP-enabled online retail platforms consistently show that model performance depends on data granularity, horizon, and feature richness. Ji et al. (2019) demonstrated that traditional ARIMA performed poorly on volatile SKU-level e-commerce sales (RMSE **21.93**), while XGBoost drastically reduced errors (RMSE **6.05**) and its clustered variant (C-XGBoost) improved further (RMSE **4.83**); the hybrid C-A-XGBoost achieved the best performance (RMSE **3.28**, MAE **2.52**), proving the value of clustering and hybridization[17].

Bandara et al. (2019) presented a worldwide LSTM-based approach to e-commerce sales demand forecasting utilizing Walmart.com data, conquering obstacles such as sparsity, irregular demand, and correlations between products in the hierarchy. Performance evaluation using modified Mean Absolute Percentage Error (mMAPE) showed that LSTM variants consistently outperformed classical models. For example, at the category level (1,724 items), LSTM.ALL achieved a mean mMAPE of 0.803–0.888, compared to 1.153 for ARIMA and 0.965–0.983 for ETS, while clustering-enhanced LSTM variants further reduced errors. At the super-department level (18,254 items), the LSTM.GROUP variant yielded the best mean mMAPE of 0.871, again outperforming ARIMA (1.084) and ETS (1.097) baselines[18].

Table I presents a summary of recent studies on enhanced ERP-based online retail prediction, outlining the proposed models, datasets used, key findings, and identified challenges

Research gaps: A number of knowledge gaps persist in online retail prediction powered by enterprise resource planning (ERP), despite substantial advancements in utilizing DL and ML models. Many studies focus on specific datasets, such as Walmart or UCI benchmarks, which limits the generalizability of results across diverse retail environments. Traditional models like ARIMA and tree-based ensembles often struggle with highly volatile or sparse transactional data, while DL models such as LSTM and CNN, though powerful, face challenges of scalability, interpretability, and consistency across varying time horizons. Moreover, hybrid and ensemble approaches, though promising, require further optimization to balance accuracy with computational efficiency. Improved models that can manage large-scale, diverse retail datasets in a more interpretable and resilient manner should be the goal of future research. One area that has not been thoroughly explored is the integration of real-time ERP-driven behavioural data streams with dynamic feature selection.

RESEARCH METHODOLOGY

The proposed flowchart in Figure 1 illustrates the methodology for ERP in online retail prediction using machine learning. The process begins with data pre-processing of the Online Retail III UCI dataset, which involves data cleaning, feature engineering, label encoding, and normalization through StandardAero. The preprocessed data is used to build two sets: one for training and one for testing. The next step in evaluating a CNN model's performance is testing, which follows its implementation and training on the dataset. Use error measures like MAE, MAPE, RMSE, and R^2-score to assess the results of ERP predictions in the e-commerce space.

A comprehensive breakdown of the suggested procedure is provided in the section that follows:

Data Gathering and Analysis

All online purchases made by a registered non-store retailer in the United Kingdom between December 1, 2009, and December 9, 2011, are included in Online Retail II. Selling one-of-a-kind giftware suitable for every occasion is the company's primary goal. The bulk of the business comes from wholesalers. The following is the data analysis that was conducted using EDA:

The histogram in Figure. 2, titled "Customer Purchase Frequency," displays the distribution of how often customers make purchases. On the x-axis, and can show the purchasing frequency, and on the y-axis, and can show the number of customers for each frequency. The graph clearly shows a highly skewed distribution, with a very large number of customers having a low purchase frequency, indicated by the tall bar near zero. As the purchase frequency increases, the number of customers decreases rapidly, with only a small number of customers making purchases very frequently. This pattern, where most customers are infrequent purchasers and a small group are high-frequency purchasers, is typical for many business models.

This Figure 3 bar chart shows Distribution of values in Price. The count of items within the '0' and '1' categories is shown. Both categories are shown on the x-axis, while the number of entries is shown on the y-axis. The chart indicates that the number of items in both categories is nearly equal, with category '0' having a slightly higher count of approximately 420,000 and category '1' having a count of around 380,000. The figure could be named Figure 3. Distribution of Price Categories.

Data Pre-processing

The Online Retail III UCI dataset was utilized for data preparation, which involved concatenation, cleansing, and feature engineering. The preprocessing phase included addressing missing values, correcting data types, handling null entries, and removing outliers, followed by labeling and normalization. The key preprocessing steps are summarized as follows:

Table 1: Recent Studies on Enhanced ERP in Online Retail prediction using Machine Learning

Author	*Proposed Work*	*Results*	*Key Findings*	*Limitations / Future Work*
Niu (2020)	Developed a feature-engineered XGBoost sales prediction model specifically for Walmart's Kaggle dataset.	Difference between RMSSE and LR and Ridge Regression: -0.141 and -0.113, respectively.	Traditional ML models were beaten by XGBoost with careful feature engineering, and useful insights were uncovered via feature importance analysis.	Limited to Walmart dataset; future work could extend to multi-retail datasets and cross-domain validation.
Alojail & Bhatia (2020)	Developed Ensemble-Blending based Ensemble (EBE) framework combining bagging, boosting, stacking, GBM, and Random Forest for ERP-driven behavioural analytics in e-commerce.	Achieved 76% classification accuracy, low RMSE, and improved R^2 on ERP-driven behavioural data.	ERP data streams can effectively classify buyers into "hot" and "cold"; framework supports predictive and targeted advertising.	More validation on large-scale real-world ERP datasets needed; integration with advanced data streaming technologies suggested.
Alojail & Bhatia (2020)	Framework for using ERP systems in online behavioural advertising, classifying user behaviour for targeted content delivery.	Demonstrated how ERP-driven data pipelines can enhance behavioural analytics for advertising.	ERP provides a strong backbone for behavioural analytics and targeted marketing.	Future work should explore scalability, real-time processing, and handling of massive ERP databases.
Ji et al. (2019)	Proposed clustered and hybrid XGBoost (C-XGBoost, C-A-XGBoost) for SKU-level e-commerce sales forecasting.	ARIMA RMSE = 21.93; XGBoost RMSE = 6.05; C-XGBoost RMSE = 4.83; Hybrid C-A-XGBoost RMSE = 3.28, MAE = 2.52.	Hybrid clustering + XGBoost models significantly reduced forecast errors compared to traditional and standalone ML approaches.	Limited exploration of deep learning methods; future work may include hybridization with neural networks.
Bandara et al. (2019)	Proposed global LSTM-based framework for e-commerce demand forecasting (Walmart.com), leveraging cross-series and product hierarchy correlations.	At category level: LSTM.ALL mMAPE = 0.803–0.888 vs ARIMA = 1.153 and ETS = 0.965–0.983. At super-department level: LSTM.GROUP mMAPE = 0.871 vs ARIMA = 1.084 and ETS = 1.097.	LSTM variants consistently outperformed statistical models; grouping strategies improved forecast accuracy.	Scalability to larger datasets and real-time applications not fully explored; integration with reinforcement learning suggested.

Data Cleaning and feature engineering

Feature engineering and data cleaning consume the bulk of time while doing data science and developing solutions. Conducting primary research and engaging in in-depth discussions about observations are essential steps in gathering more relevant and high-quality data to use in testing and analyzing the present models. Variegated input data with complicated features may be manageable for certain model types. The ability of a simple RFM (Recency, Frequency, Monetary) based model to accommodate more domain-specific features is limited, for instance. Data including cancellation records has been separated into its own column and then removed since it does not impact the prediction performance. As an added bonus, and deleted any records where the unit price is zero. Multiplying the 'quantity' and 'price' values yields a new characteristic called revenue.

Label Encoding

Label encoding is a method for numerically representing categories that is utilised in data analysis and ML. Because the vast majority of machine learning models are numerical in nature, it is often invaluable when dealing with numerically-intensive procedures.

Normalization with Standard Scaler

Given the different scales of each descriptor, the dataset was standardized using the StandardScaler () method to transform the data so that the mean of the resulting distribution is zero and the standard deviation is one. This transformation is achieved by subtracting the mean value of each observation and dividing by the standard deviation, as shown in Equation (1):

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

Where the feature's converted value (z), the original values (x) of each descriptor, the mean (μ), and the standard deviation (σ) are all defined in the dataset.

Data Splitting

Therefore, around 70% of the data was used to create a training set, while the remaining 30% was used to create a test set.

Proposed Convolutional Neural Network (CNN) Model

This paper suggests a supervised deep learning algorithm, namely a CNN, to make predictions in online retail systems with an ERP. A CNN is a DL model, an ANN that theorises image patterns and is frequently applied to image processing and image recognition. Each layer of a CNN contributes to the final product. Pooling reduces the number of input parameters, while the convolutional layer converts images to numbers. DL algorithms, of which CNN is a subset, are well-suited to algorithms that deal with images and their processing. The fully connected, convolutional, and pooling layers are some of its many components. Because their design is based on how the human brain processes visual information, CNNs are able to effectively extract hierarchical patterns and spatial dependencies from images. By using t, can determine the size of a convolutional layer's output. The length of output in this case is 5. Overall, the duration of the output is as follows,

With nx being the input signal length and nh being the filter length, the output size can be expressed as $nx = 2P - nhS + 1$, or as n x + 2 P − nh S + 1.

The mathematical operation known as convolution (Conv_Op) has widespread application in computer vision, signal processing, and image processing. Use it to combine two signals or functions into one, and the resulting signal indicates the comparative importance of the two signals based on their respective shapes. Convolution, which is applied in computer vision, involves the extraction of features within the image using CNNs.Equation (2) provides a precise definition of the convolution operation:

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m] g[n-m] \qquad (2)$$

Functions f and g, which might be discrete or continuous, and the index of place or time in the output signal are represented by n in this case. The symbol ∗ stands for the processing of convolution. In the scenario when the input signals are discrete, rewrite Equation (3) as:

$$(f * g)[n] = \sum_{m=-\infty}^{\infty} f[m] g[n-m] \Delta m \qquad (3)$$

n indicates the location or time of the output signal, while f and g might be discrete or continuous functions, respectively. A ∗ stands for a convolution operation. If the input signals are discrete, rewrite Equation (4) as:

$$(f * m)(t) = \int_{-\infty}^{\infty} f(\tau) g(t-\tau) d\tau \qquad (4)$$

Where the output signal's time index is denoted by t.

Evaluation Metrics

Model evaluation is an essential part of ML projects since it is used to retrieve information about the performance of models, as well as enabling the clear presentation of the results. Four performance measures were applied to evaluate the models in this research which included R^2, MAE, RMSE, and MAPE.

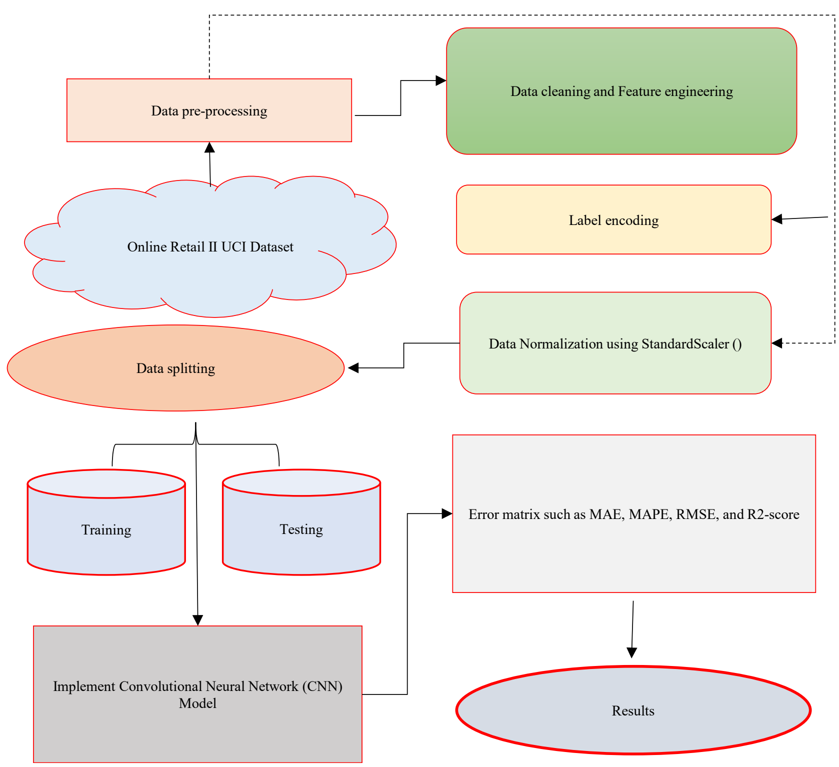

Fig 1: Proposed Flowchart for ERP in Online Retail prediction using Machine Learning

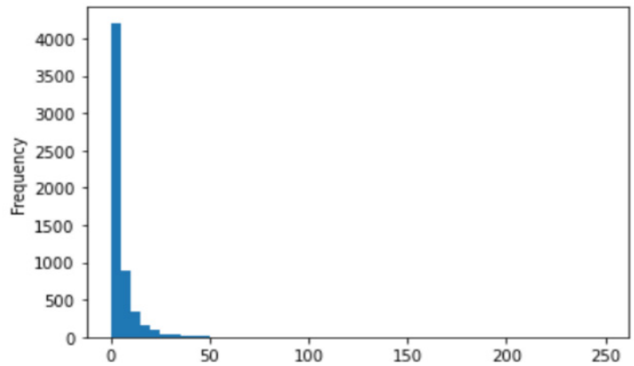

Fig 2: Customer Purchase Frequency Histogram

Fig 3: Distribution of Values in Price

R-Squared

R 2 is the degree to which the regression model fits the data. The higher the value of R2, which can take on values between 0 and 1, the better the data fits the model. With an R2 value of 1, the model provides an ideal prediction of the response data, while an R2 value of 0 indicates that the model does not anticipate any variability of the response data with respect to the mean value of the data. To determine R2, use Equation (5):

$$R^2 = \frac{\sum_{i=1}^{n}(y_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \tag{5}$$

MAE (Mean Absolute Error)

The MAE is a widely applied index to measure the predictive model accuracy. It estimates the mean size of mistakes in a pool of projections, but does not take into account their direction. Performance is improved when the MAE is lower. To find the MAE, use Equation (6):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(y_i - y_i^P)\right| \tag{6}$$

Where,

Y is the actual value,

Y stands for the expected value, and n for the total number of observations.

RMSE (Root Mean Squared Error)

The formula for this statistic is the MSE. A model's RMSE quantifies the degree to which the model's forecasts deviate from the observed data. Diminutive RMSEs indicate better model performance. Equation seven gives the RMSE (7):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^{\dot{P}}\right)^2} \tag{7}$$

MAPE (Mean Absolute Percentage Error)

The MAPE algorithm calculates the percentage of error, which is the average percentage by which predictions deviate from their intended goals in the dataset. As a percentage, MAPE represents the MAE that was returned Equation (8).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} / \left(\frac{\left(y_i - y_i^{\dot{P}}\right)^2}{y_i}\right) / *100 \tag{8}$$

The combination of these metrics gives information on whether the model is accurate and effective in predicting the target variable.

RESULTS AND DISCUSSION

The study describes the experimental setup, shows how well the suggested model performs throughout training and testing, and emphasises its processing and evaluation abilities. He proposed CNN model was tested on the system with a multi-core CPU, high-end graphics cards, and enough RAM to work with large datasets. Windows 32/64-bit was the platform on which it was done, and Python was the main language used in the programming. Jupyter Notebook facilitated model development, while libraries like BeautifulSoup, NLTK, Pickle, and Streamlit supported data processing and visualization. Table II shows the results of the proposed CNN for improving ERP-based online retail prediction with the Online Retail II dataset. With a minimum variation between predicted and actual values of 2.814 and a low MAE of 2.277, the model displayed high predictive ability. A slight percentage mistake in forecasts was reflected by the MAPE of 13.72%. Moreover, with a R^2 value of 94%, the model proved that the CNN was effective in accurately predicting online retail sales and demonstrated its great capacity to explain the variability in the transactional data.

Results from a machine learning model's execution are likely depicted in Figure 4's scatter plot, which displays the correlation between the two sets of numbers. By counting

Table 2: Classification results of the model for Enhanced ERP in Online Retail prediction using Online Retail II Dataset

Matrix	*Convolutional Neural Network (CNN)*
MAE	2.277
RMSE	2.814
MAPE	13.72
R2	94

the number of open circles, and can be shown that there are a thousand data points in the plot. The equation that best fits the data (the solid blue line) is Output = 0.98 * Target + 0.33, which is a linear regression. The output and target values exhibit a robust positive linear association, as indicated by this equation. In an ideal fit, when Output is equal to Target, the model's predictions are extremely close to the target values, as shown by the dashed grey line Y = T.

The learning curve, shown in Figure 5, shows how the model's performance on the train and test sets changes as the training set size increases. Initially small, the training error (blue line) steadily increases in size, whereas the testing error (red line) begins huge and subsequently shrinks. This indicates the model is improving as it's trained on more data. At a training set size of 850, the MAE for the test phase is approximately 2.3, and the MAE for the train phase is around 2.074. The gap between the two curves suggests there is still a small amount of variance, and the model could potentially improve with more data or further tuning.

Comparative Analysis

The effectiveness of the proposed CNN model is assessed through a comparative accuracy evaluation with other existing models, as presented in Table III. This presents a comparison of different ML and DL models for enhancing ERP-based online retail prediction using transactional data. Among the models evaluated, the Decision Tree (DT)

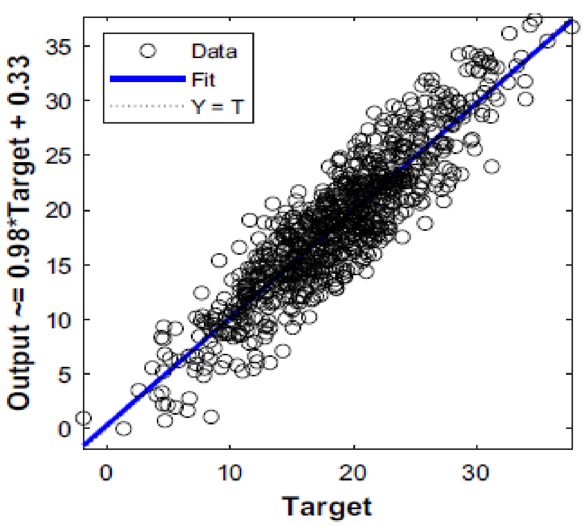

Fig 4: Scatter Plot for CNN Model

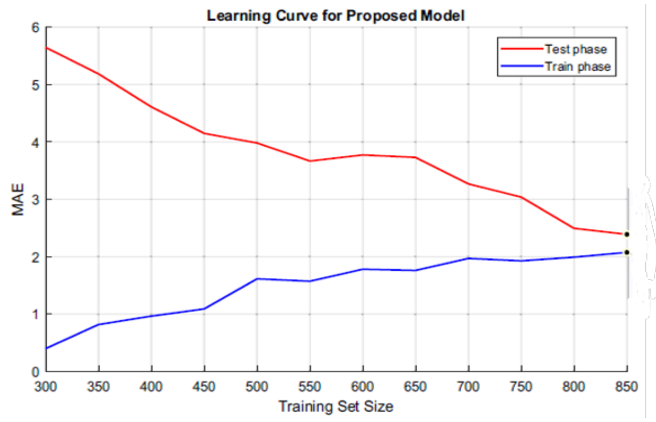

Fig 5: Learning Curve for Proposed CNN

Table 3: Comparison of Different Machine Learning and deep learning Models for Enhancing ERP in Online Retail prediction

Model	*R2*	*MAE*
DT[19]	54.7	2101.33
GBM[20]	85	55,133.85
RF[21]	87	-
CNN	94	2.277

achieved an R^2 of 54.7 with a MAE of 2101.33, indicating moderate predictive capability. The GBM performed better, achieving an R^2 of 85 but with a relatively high MAE of 55,133.85, suggesting some variability in prediction errors. The RF model was also very powerful and had an R 2 of 87, but there was no reported MAE. Interestingly, the proposed CNN was the most effective with the highest R 2 of 94 and lowest MAE of 2.277, which is more accurate and efficient to predict online retail transactions.

A higher predictive performance in comparison to traditional machine learning models is a key benefit of the proposed CNN model, which has a R 2 of 94. This is because ERP-enabled e-commerce systems are able to produce more accurate and dependable sales forecasts since they can grasp the complicated and non-linear correlations included in Online Retail II data. It is a robust solution for real-world retail prediction tasks, and the model's outstanding performance decreases prediction mistakes, boosts decision-making for business operations, and displays resilience when dealing with large-scale data.

Justification and Novelty

The increasing demand for trusted sales forecasting in ERP-powered e-commerce platforms is driving this research. However, conventional machine learning algorithms have a hard time understanding the intricate, non-linear correlations present in massive amounts of transactional data. Inaccurate forecasts can lead to poor inventory management, increased operational costs, and reduced customer satisfaction, making advanced predictive models essential for sustainable business growth. The novelty of this research stems from the application of a CNN to structured retail transaction data, a domain where CNNs are rarely employed, as they are typically reserved for image and signal processing tasks. By leveraging CNN's capability to extract hierarchical features and recognise intricate patterns, this work demonstrates superior predictive accuracy compared to conventional models such as DT, Gradient Boosting, and RF, thereby introducing a new DL perspective for ERP-based retail forecasting and decision-making.

CONCLUSION AND FUTURE STUDY

Online shopping has been expanding at a rapid pace in recent years, and there is a wealth of data about consumer habits stored on websites. User preferences might be revealed through the e-commerce platform's operational behaviours. Researchers in both academia and business have made great strides in understanding how to mine user preferences through observation of their actions. Combining methods often greatly improves an algorithm's generalizability, which in turn improves the prediction effect. With a R^2 value of 94, the suggested CNN model far surpasses Decision Tree, GBM, and RF, three conventional ML models, according to the comparison results. The CNN achieved such impressive results because it was trained using the Online Retail II dataset, which contains intricate patterns. Then, it underwent excellent feature selection, which eliminated irrelevant variables while retaining the most important ones. By removing extraneous variables, the model enhanced prediction accuracy while simultaneously decreasing computational complexity. This proves that a reliable and efficient framework for online retail prediction enabled by ERP may be achieved by integrating CNN with robust feature selection. It would be more beneficial to shift the emphasis from the algorithm to the variable choices in further study. Cluster analysis and feature generation are just two of many areas that have room for development.

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