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Predictive Analytics for E-Commerce Sales Profitability using ResNet and Cloud Integration

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Abstract

The proposed framework for predicting e-commerce sales profitability using ResNet and cloud integration has demonstrated exceptional performance in classifying transactions as Profitable or Non-Profitable. With key performance metrics such as accuracy (99.5%), precision (99.7%), recall (99.8%), and F1-Score (99.6%), the model offers highly reliable predictions. Additionally, the False Positive Rate (FPR) and False Negative Rate (FNR) are minimal, confirming the model's precision and reliability in real-world applications. The confusion matrix further supports the model's effectiveness in distinguishing between profitable and non-profitable sales transactions. Future projects will concentrate on refining the framework by adding seasonal patterns, consumer opinion, and product demand forecasting to the model in order to make it more accurate and responsive. The model will be implemented in a real-time production setting using AWS Lambda and other cloud services to maintain effortless scalability. Besides comparing performance with other sophisticated models such as Transformers and LSTMs, it will assist in measuring their ability to predict profitability. The model will be also expanded to process multi-class classification to provide finer-grained understanding of the multiple levels of profitability to augment its usefulness for business.

***Keywords**: E-commerce Profitability Prediction, ResNet, Cloud Integration (AWS), Data Processing, Sales Classification, Predictive Analytics, E-commerce*

Introduction

The e-commerce industry has experienced rapid growth worldwide, fundamentally transforming consumer behavior and generating vast amounts of transactional data every day [1]. This expansion necessitates that organizations develop the ability to accurately interpret sales data to enhance profitability and sustain competitive advantage [2]. The increasing size, diversity, and complexity of sales transactions require advanced predictive analytics tools capable of optimizing inventory control, promotional efforts, and dynamic pricing strategies [3]. Additionally, e-commerce platforms must integrate real-time data from multiple sources—including customer behavior, social media sentiment, and supply chain logistics—which demands models capable of processing high-velocity and high-variety data [4].

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Machine learning models that forecast profitability empower businesses to anticipate sales trends, improve demand planning, and make data-driven decisions that enhance operational efficiency and reduce costs [5]. However, many existing models are challenged by the scale and complexity of e-commerce data, resulting in limited forecasting accuracy and poor scalability [6].

Traditional approaches such as Logistic Regression, Decision Trees, Random Forests, and Support Vector Machines (SVM) have been applied for sales prediction and classification tasks [7][8]. Although these models offer simplicity and interpretability, they often depend on manual feature engineering and lack the ability to capture nonlinear relationships and complex temporal patterns present in e-commerce datasets [9]. For instance, Decision Trees are prone to overfitting in noisy data environments, while SVMs struggle to model high-dimensional nonlinear dependencies effectively [10]. Moreover, many legacy models fail to account for dynamic pricing, seasonal fluctuations, and the diverse fulfillment channels inherent to e-commerce [11]. These limitations underscore the need for a more sophisticated and scalable solution capable of extracting intricate patterns from large-scale heterogeneous data [12]. Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated superior capabilities in learning hierarchical data representations and reducing reliance on manual feature extraction [13]. Specifically, Residual Networks (ResNet), with their residual connections, effectively address the vanishing gradient problem, enabling deeper networks to capture complex features within e-commerce data [14][15].

Leveraging cloud computing platforms like Amazon Web Services (AWS) further enhances the scalability and real-time processing capabilities essential for modern e-commerce analytics [16]. AWS services such as S3 provide robust and scalable data storage, while EC2 offers flexible computing resources for model training and deployment [17][18]. This cloud infrastructure enables horizontal scaling, fault tolerance, and rapid elasticity, which are crucial during peak sales periods like holiday seasons [19]. The proposed framework integrates ResNet with cloud computing to efficiently handle transactional, customer, product, and market data, facilitating real-time, high-accuracy profitability prediction [20]. This novel combination surpasses traditional models in both precision and scalability, positioning it as a powerful tool for e-commerce decision-making [21]. The system also paves the way for future enhancements involving seasonal trend analysis, consumer sentiment incorporation via natural language processing, and multi-class profitability classification for more granular business insights [22][23]. Furthermore, it establishes a benchmark for evaluating other advanced models such as Transformers and LSTMs within e-commerce predictive analytics [24]. Through cloud-based deployment using AWS Lambda and other services, the framework supports seamless integration and adaptability, making it a valuable asset in the rapidly evolving e-commerce landscape [25].

1.1 Objectives

- Create a scalable predictive model utilizing ResNet to classify e-commerce sales transactions as Profitable or Non-Profitable from transactional, product, and customer data.
- Utilize cloud integration (AWS) for storing and processing big e-commerce datasets, facilitating real-time analysis and ensuring smooth data handling through services such as AWS S3 and EC2. Facilitate business decision-making by delivering actionable insights through real-time profitability predictions, improving inventory management, pricing strategy, and marketing campaigns.

2. Literature Survey

Utilizing the theoretical foundation of Communication Privacy Management (CPM), recent research investigates commonly recognized privacy concerns in mobile commerce, such as data collection, user control, awareness, unauthorized secondary use, improper access, and a newly adapted dimension of location tracking [26]. These studies also examine trust in mobile advertisers and attitudes toward mobile commerce, which have been shown to significantly predict approximately 43% of the variance in mobile commerce engagement [27]. This highlights how privacy perceptions and trust are critical factors influencing consumer behavior in mobile and e-commerce settings [28]. As mobile technologies evolve rapidly, privacy concerns continue to shift, necessitating ongoing research to address challenges related to personalized marketing, data sharing, and regulatory compliance [29]. Integrating privacy management theories with consumer behavior models enhances the understanding and prediction of engagement in mobile commerce [30].

The importance of Big Data Analytics (BDA) in e-commerce has grown substantially over recent years, yet its theoretical and practical foundations remain insufficiently explored [31]. Systematic literature reviews reveal that BDA’s distinct features—volume, velocity, variety, veracity, and value—pose unique challenges and opportunities for e-commerce businesses [32]. Scholars propose interpretive frameworks that define BDA concepts, explore its types, and highlight the business value and challenges within the e-commerce landscape [33]. These frameworks stimulate scholarly discussions about future research directions and practical applications, emphasizing the transformative potential of BDA in customer personalization, inventory management, and supply chain optimization [34]. However, significant obstacles persist, including data governance complexities, integration issues, and talent shortages, which hinder widespread adoption and effective utilization of BDA [35][36].

A promising approach to address these challenges is the Big-Data Hybrid-Data-Processing Lambda Architecture, which merges low-latency real-time data processing with high-throughput batch processing frameworks like Hadoop, deployed across massively distributed infrastructures [37]. This architecture treats real-time and batch processing engines as autonomous, collaborative multi-agent systems to balance speed and comprehensive data coverage [38]. The Multi-Agent Lambda Architecture (MALA) proposed for e-commerce analytics addresses the latency issues of Hadoop MapReduce by enabling simultaneous speed-layer processing for time-sensitive requests [39]. Meanwhile, the batch layer runs in parallel to ensure complete data analysis by blending streaming and historical data using weighted voting methods [40]. The architecture also tackles the cold-start problem in streaming services by initializing streams with offsets from historical data, enhancing early-stage prediction accuracy [41]. High-velocity data ingestion challenges are managed via distributed message queues that support scalable and resilient data pipelines [42].

Additionally, a multi-agent decision-maker component integrated into the MALA stack serves as a gateway for orchestrating efficient data analytics workflows [43]. Empirical studies confirm the effectiveness of this hybrid model, as demonstrated by implementing a suite of e-commerce features that improve predictive accuracy and system responsiveness [44]. Current research is exploring enhancements such as adaptive learning algorithms and edge computing integration to further reduce latency and optimize real-time processing [45]. Overall, these innovations represent a major advancement in the development of scalable, robust, and responsive big data analytics architectures tailored to the evolving needs of modern e-commerce platforms [46].

2.1 PROBLEM STATEMENT

E-commerce plays a key role in driving business success in today's digital economy, making the performance of e-commerce websites critical to organizational competitiveness [47]. These websites generate massive volumes of data that can be leveraged for comprehensive performance evaluation and optimization [48]. While many website evaluation methods have been proposed, the impact of social media factors, such as user sentiment and engagement on platforms like Twitter, is often overlooked in traditional assessments [49]. This study proposes the use of Twitter data in big data analytics to develop new performance indices that better reflect real-time customer interactions and sentiments, thereby enhancing website performance evaluation [50]. Additionally, the paper introduces an ontology-based big data analytics framework and a service-oriented architecture designed to improve business intelligence (BI) systems. By focusing on characteristics such as temporality, expectability, and relativity, the approach aims to align BI capabilities with the dynamic expectations of customers and decision makers. These developments hold the potential to advance research and practice in business analytics, big data science, and enterprise information systems.

3. Proposed Methodology

The proposed framework outlines the predictive analytics process applied to E-commerce sales data. The process begins with Data Collection, where relevant information from e-commerce platforms is gathered, including transactional records, customer details, and product information. This data is then passed through the Pre-processing stage, where Normalization is applied to standardize numeric values and Missing Value Imputation addresses any missing data. The clean, structured data is stored in the Cloud for scalable storage and processing, ensuring ease of access for analysis. AWS S3 and EC2 are used for storing and processing large datasets efficiently, while Apache Spark or AWS Lambda enable real-time data processing and analysis, allowing businesses to track sales trends instantly. At the core of the framework is Predictive Modeling Using ResNet, where a Residual Network is employed to classify sales transactions as Profitable or Non-Profitable based on various features. The model's output is then visualized through Reporting & Insights, using dashboards to present key metrics and facilitate data-driven decision-making. This framework equips businesses with accurate predictions and valuable insights to optimize inventory management, improve marketing strategies, and refine product launches.

3.1 Data Collection

The data collection phase for this framework involves gathering e-commerce sales data from multiple platforms such as Amazon, Flipkart, Myntra, and others, which includes detailed information about each transaction. This data encompasses product features like SKU codes, design numbers, stock levels, categories, sizes, and colours, along with financial details such as MRPs across different stores (e.g., Amazon MRP, Myntra MRP) and amounts paid by customers for individual purchases. Additionally, transactional parameters like sales dates, quantities, fulfilment methods, B2B status, and customer demographics are collected. Data from both fulfilment methods (Shiprocket and INCREFF) is incorporated to analyse profitability and identify trends as shown in Figure 1. This comprehensive dataset is essential for understanding the dynamics of e-commerce sales and profitability, providing the foundation for predictive modelling and business decision-making.

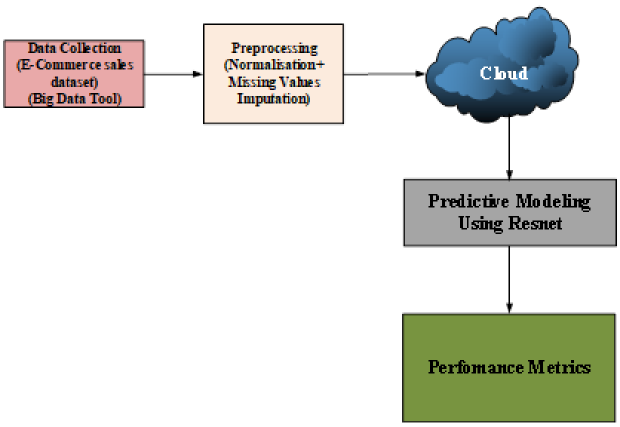

Figure 1: Proposed framework

3.2 Preprocessing

Pre-processing needs to be carried out to prepare the dataset for analysis, with precision and consistency. Pre-processing includes normalization and imputation of missing values. Normalization brings numerical features to the same scale so models will not be biased due to scale differences between features. Imputation of missing values prevents missing values in data from biasing analysis by filling in the blanks with meaningful estimates. Additionally, extraneous data as well as outliers are removed in this step so that model performance is improved.

a. Normalization

This scaling process standardizes numeric features to a standard range so none of the features dominate others due to different scales or units. Common techniques include Min-Max scaling, scaling values to a standard range (e.g., 0 through 1), and Z-score normalization, scaling data by normalizing it from the mean and scaling to unit variance.

Min-Max Scaling: This method converts data into a fixed scale, usually between 0 and 1, by subtracting the minimum value and dividing by the range (max - min) of the data.

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

Z-Score Normalization*:* This process normalizes data through the process of subtracting the mean and dividing by the standard deviation, so that the distribution has a mean of 0 and a standard deviation of 1.

$$X_{norm} = \frac{X - \mu}{\sigma} \tag{2}$$

were, μ is the mean, and σ is standard deviation.

b. Missing Value Imputation*:* To ensure dataset integrity, missing values are replaced with approximated ones. Popular methods include K-nearest neighbours (KNN) imputation, which approximates missing values by averaging the K nearest data points, and mean imputation, which replaces missing values with the mean of the available data.

Mean Value Imputation: Replace missing value with mean of available data.

$$X_{\text{imputed}} = \mathrm{mean}(X_{\text{available}}) \tag{3}$$

K-Nearest Neighbours (KNN) Imputation: Use average value of K nearest neighbours to impute missing value.

3.3 Cloud Integration

Cloud Integration is a method of storing and processing large volumes of data using cloud infrastructure in an effective way. The services provide scalability and deployment of predictive models, allowing immediate and efficient data processing. AWS S3 is used to store vast quantities of E-commerce sales data efficiently and securely. The data will be uploaded to AWS S3 buckets so that it is readily accessible for pre-processing, analysis, and training of models. Since AWS S3 has a scalable architecture, it means that as your data grows, the storage capacity also increases automatically without the need to manually intervene. It shall also be a single source repository, thus being easily combined with AWS EC2 for model training and data processing. Additionally, AWS S3 facilitates data encryption and access control, hence the security of sensitive customer and sales data. Through the usage of AWS S3, our system acquires a secure, affordable means of processing massive amounts of data and achieving seamless scalability.

3.4 Predictive Modeling using ResNet

ResNet (Residual Network) is a deep network architecture mostly employed in image and time-series analysis based on residual connections to facilitate better training of deep neural networks. Following is the predictive modelling process with ResNet along with the corresponding formulas with architecture diagram given in Figure 2 below.

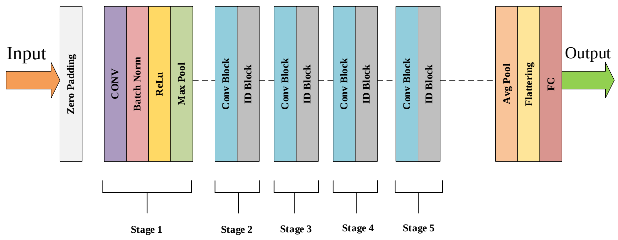

Figure 2: ResNet Architecture

1) Data Preparation and Building the ResNet Architecture

The purpose of data preparation is to pre-process the dataset by normalizing the numerical values, filling in missing values, and making it ready for use with the ResNet model. This makes sure that the data is clean, standardized, and suitable for use with the requirements of the model. For creating the ResNet architecture, the aim is to create a network with residual links, enabling the gradients to flow well through deep layers during training, avoiding the problem of vanishing gradients.

ResNet's core idea is the residual block, which allows the network to use an identity mapping to feed the input straight into a deeper layer while avoiding one or more levels. The mathematical Residual Block Formula is,

$$\text{Output} = F(X, \{W_i\}) + X \tag{4}$$

X is the input to the residual block, $F(X, \{W_i\})$ represents the learned transformations (convolution + activation functions), W_i are the weights of the convolutional layers.

2) Forward Propagation in ResNet

The forward pass in ResNet involves computing the output through multiple layers with each block following the formula, Output $= F(X, \{W_i\}) + X$. After the residual block, the data passes through an activation function like ReLU (Rectified Linear Unit) and a batch normalization layer, for which the mathematical representation is,

$$\mathrm{ReLU}(X) = \max(0, X) \tag{5}$$

3) *Loss Function*: Minimize the error between predicted and actual outputs by optimizing the model weights. The Mean Squared Error (MSE) loss function commonly used is,

$$L = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{6}$$

were, N is the number of samples, y_i is the actual value, $\hat{y}_i$ is the predicted value.

For classification task, Cross Entropy Loss is used,

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{7}$$

were, C is the number of classes, y_i is the actual class label (one-hot encoded), $\hat{y}_i$ is the predicted probability for the class i.

4) *Optimization (Gradient Descent):* Optimize the weights of the residual blocks using backpropagation and gradient descent mathematically formulated as,

$$W_i = W_i - \eta \frac{\partial L}{\partial W_i} \tag{8}$$

η is the learning rate, $\frac{\partial L}{\partial W_i}$ is the gradient of the loss function with respect to the weight W_i.

5) *Training and Evaluation:* Train the ResNet model by iteratively updating the weights until convergence. The model is trained over several epochs, with the performance evaluated using validation data at each step. Key performance metrics include accuracy, precision, recall, and F1-score for classification tasks, or R-squared for regression tasks.
6) *Prediction:* Once the model is trained, it is used on unseen data to make new predictions,

$$\hat{y} = \mathrm{ResNet}(X) \tag{9}$$

were, $\hat{y}$ is the predicted output for the input X.

4.Rresult and Discussion

The model clearly exhibits good performance in labelling e-commerce sales Profitable or Non-Profitable, as highlighted by the ROC curve with a high degree of classification precision at low rates of false positives. The performance measure indicates precision, recall, and F1-score, revealing accurate and balanced prediction. The model's ability to distinguish between the classes with a minimal amount of incorrect classifications is shown in the confusion matrix. Furthermore, the model is quite dependable in its predictions, as evidenced by the extremely low False Positive Rate (FPR) and False Negative Rate (FNR). All things considered, the framework provides a solid way to classify the profitability of e-commerce.

4.1 Confusion Matrix

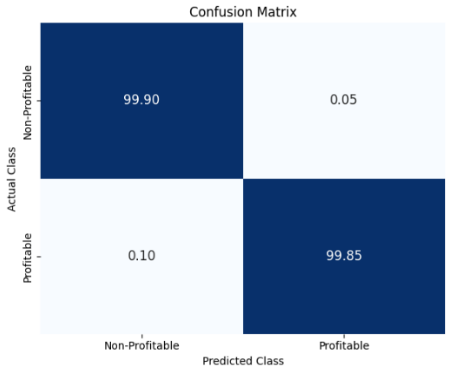

Figure 3: Confusion matrix

The confusion matrix illustrated here in figure 3 is the performance of the predictive model in identifying Profitable and Non-Profitable e-commerce sales transactions. The matrix indicates that 99.90% of the Non-Profitable sales were correctly labelled as Non-Profitable with only 0.05% of them mislabelled as Profitable (False Positive). Likewise, 99.85% of Profitable transactions were accurately classified, with a mere 0.10% being incorrectly classified as Non-Profitable (False Negative). These findings indicate a very precise model, with only a few misclassifications. The high proportion of true positives and true negatives indicates that the predictive model derived from ResNet is well on its way to identifying the profitability of sales transactions, which will enable businesses to make effective decisions in inventory management, pricing, and marketing strategy.

4.2 Performance Metrics

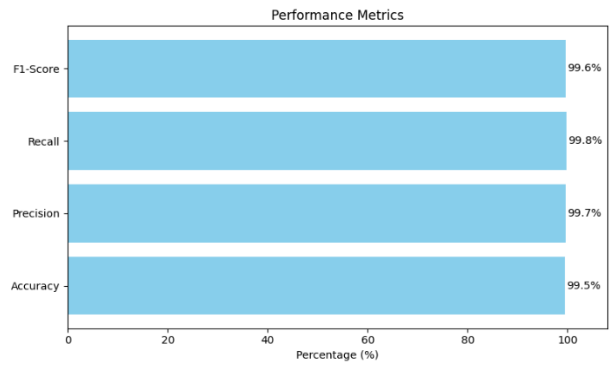

Figure 4: Performance metrics

The model used as shown in Figure 4 is classifying profitable and non-profitable sales transactions does extremely well according to its statistics, as shown in the graph. At 99.5% accuracy, the model has correctly identified most transactions. At a precision of 99.7%, the model appears to be extremely precise in identifying successful trades. At a recall rate of 99.8%, the model successfully finds the most profitable sales. A very well-balanced performance in identifying both profitable and unprofitable sales is reflected by the F1-Score of 99.6%.

4.3 False Positive Rate and False Negative Rate

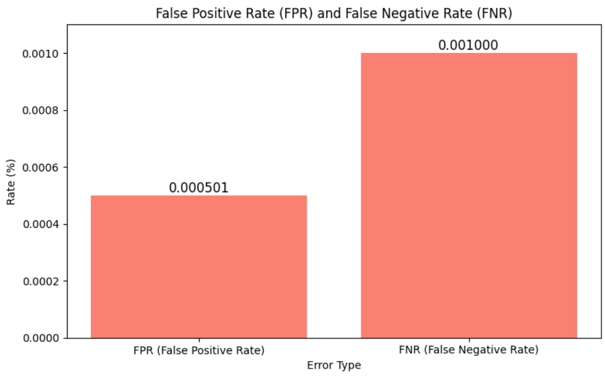

Figure 5: False Positive Rate and False Negative Rate

The chart in Figure 5 shows the False Positive Rate (FPR) and False Negative Rate (FNR) for the model's performance. The FPR is 0.000501%, which means that the model has a very low rate of misclassifying non-Profitable sales as Profitable. The FNR is 0.001000%, which means that the model makes an extremely small number of false negatives, i.e., it hardly ever misses a profitable sale. Both the rates are extremely low, which signifies that the model is very precise with its classification with zero errors.

4.4 ROC Curve

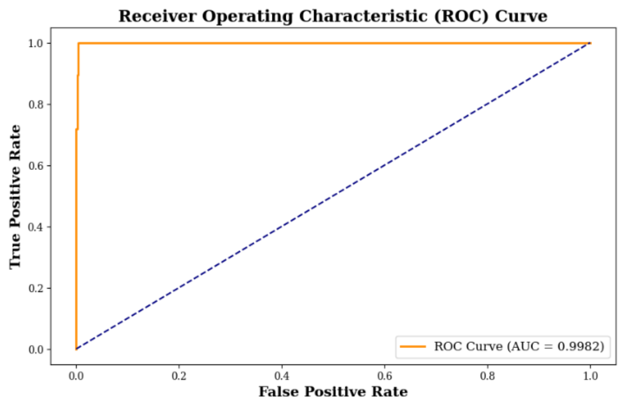

Figure 6: ROC Curve

The Receiver Operating Characteristic (ROC) curve of the suggested framework depicts high classification performance in the prediction of Profitable vs non-Profitable sales transactions. The model boasts outstanding discrimination ability between the two classes with an AUC (Area Under the Curve) value of 0.9982. The curve illustrates that the True Positive Rate (TPR) rises significantly with negligible False Positive Rate (FPR), displaying high accuracy in predictions as shown in Figure 6. This high AUC value also validates the model's effectiveness in processing e-commerce sales data and its performance in profitability classification.

Conclusion and Feature Enhancement

The intended framework for the prediction of profitability of e-commerce sales based on ResNet and cloud integration has been shown to be highly accurate in classifying transactions into Profitable or Non-Profitable. With accuracy (99.5%), precision (99.7%), recall (99.8%), and F1-Score (99.6%), the model is highly efficient at predicting profitability. The False Positive Rate (FPR) and False Negative Rate (FNR) are close to zero, which suggests that the accuracy of the model stands validated. Future development will further include other aspects like seasonal trends and customer data for better predictions. The model will be deployed into an actual production setup with the help of cloud platforms such as AWS Lambda. Cross-comparisons with other state-of-the-art models such as Transformers and LSTMs would also assist in their performance assessment for profitability prediction. Scaling up the model to multi-class classification may provide more detailed insights into various classes of profitability.

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