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A Low-Cost Automated Intervention Framework for Customer Retention in Data-Constrained E-commerce Startups

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Abstract:

Small E-commerce companies operate in highly competitive online selling markets, yet most sophisticated consumer forecasting algorithms are developed to support large platforms that have numerous historic forecasts as well as high computing power. Such business-level ones are often difficult to use, costly and difficult to instal in locations where there is limited data or technology. Due to this reason, there are still numerous small organisations that use primitive working tools of analytics and make a decision after events rather than in real-time predictive intelligence. This article explains how the Light Predict framework, a small scale and low cost consumer prediction and automated symptomatic framework, was designed to suit the environments with the minimal data and limited resources. The system monitors the real time user habits such as clicking, duration of time in a session and shopping cart interaction. It subsequently transforms this raw data into organised session level items such as session velocity, cart hesitation time, and interactions patterns. The lightweight machine learning models (such as Random Forest, XGBoost, and LightGBM) are used to determine the likelihood of an individual purchasing anything or leaving. Prediction results would be used to automatically initiate activities in the system such as dispatching discount offers and retention messages. The suggested architecture is centred on the modular architecture, easy to implement and low cost infrastructure that is suitable to the e-commerce businesses that are new.

Keywords: E-commerce Analytics, Purchase Prediction, Random Forest, Customer Retention, Real-Time Analytics

1. INTRODUCTION:

Customer orientation in the business is something that a business must handle differently due to the rapid pace that digital commerce has taken [1]. It is also now possible to sell using small business through the internet. More and more contemporary online shops are turning to predictive analytics to discover the behaviour of the customers, predict their likelihood to purchase an item, and retain them [2]. Large companies apply complex machine learning solutions that operate in real-time and examine massive data volumes to improve their marketing campaigns and provide people with an even more personalised experience [3, 4]. Nevertheless, such systems of big businesses usually require a large amount of aged information, robust computer networks, and dedicated teams of engineers to develop it [5]. Small and new online stores, on the other hand, have a considerable amount of difficulties to face. Complex predictive systems are difficult to put together in a market where users are limited, data available about the past is minimal, funds are limited and technical expertise is limited [6]. This is the reason why most small businesses perform static analytics dashboarding and make decisions manually rather than basing them on up-to-date and automated knowledge [7]. We require inexpensive and easy to use solutions, which can work well with small data volumes as there exists a disparity between the advanced technology in the field of prediction and the issues that small companies encounter [8]. It is mentioned in this paper because this was the concept and the design of Light Predict, a simple and real-time client behaviour prediction and action-taking system, which was designed specifically to run on an e-commerce platform with only modest resources [9]. The offered solution uses real-time clickstream data, converting unstructured interaction data to structured variables at the session level [10, 11], and uses simple machine learning models to estimate the purchasing intentions of a consumer and the chances of his or her exit [12].

The model instructs the system to automatically computer-generated business processes that had been established earlier like sending out notifications of sales and retaining customers [13]. It is not a piece of work that creates a novel predictive algorithm. Rather it is discussing system architecture, how to apply it, and how to bring behavioural modelling and automated business logic to bear in practise [14]. The significant objective is to create an affordable, scalable and modular time analytics software with real application in the initial phase of internet commerce [15].

1.1 Key Contributions:

- The first lightweight framework that works from start to finish in startup environments
- Full deployment specs with a cost breakdown (around ₹600–1,500 per month)
- Feature engineering method that works best with small amounts of data
- A comparison that shows the benefits for settings with limited resources

2. LITERATURE REVIEW

The ability to see what clients are going to buy in real time is a revolutionary tool for ecommerce platforms. It facilitates more effective inventory management, tailored marketing, and increased sales [1], [2]. Many large retailers employ powerful deep learning clusters to accomplish this [3, 4]. However, small e-commerce firms face their own challenges, including insufficient funds for computers, insufficient data, and inadequate GPU infrastructure [5, 6]. Many individuals require lightweight frameworks capable of producing highly accurate forecasts on inexpensive hardware or modest cloud instances [7, 8].

In the past, we used group analysis of historical data to predict what consumers would purchase; today, we perform this in real time during the session [9, 10]. Startups require models that can determine a user's intent score based on how long it takes them to complete a session based on their current clickstream. Research on models like Random Forest, XGBoost, and logistic regression conducted between 2020 and 2025 is examined in this review. For companies that must adapt, models that are simple to use and comprehend are crucial [13, 14]. This evaluation provides a targeted guide for e-commerce implementations with low resources because it excludes research that concentrates on big data and relies on GPUs [15].

This paper also discusses how predictive modelling can be used to generate revenue through automated methods such as conversation triggers and dynamic discounting [16], [17]. In order to provide a comprehensive picture of how small companies might apply advanced machine learning without having to pay the high costs of typical "big data" methods, this paper examines the junction of computational efficiency and business relevance [18, 19].

The most significant findings from 19 significant research studies that examined how to predict what lamp consumers will purchase are displayed in Table 1.

Table 1: Comparison of Existing Survey with Our Work

Author(s)	Year	ML Model Used	Dataset	Key Finding	Limitation
Baati et al. [20]	2020	RF, Naïve Bayes, C4.5	Online shopper sessions	86.78% accuracy in realtime prediction	No live traffic testing
Alshehri et al. [21]	2021	RF, XGBoost, AdaBoost	23 MOOC runs	82–95% accuracy achieved	High data requirements
Tokuç et al. [22]	2024	LightGBM	Clickstream data	Efficient for largescale data	High dimensionality
Wang et al. [23]	2024	Neural Network	JD.com data	85.38% accuracy	Big data dependency
Hesvindrati et al. [24]	2025	RF, GBDT, LR	7 months of Logs	Behavior based prediction effective	Lacks resource data
Pérez [25]	2025	Extra Trees, RF	12,546 sessions	93.99% accuracy achieved	Generalization unknown
İçer et al. [26]	2020	Not Specified	E-commerce users	Purchase likelihood prediction	Sparse model details
Requena et al. [27]	2020	RF, XGBoost,	Clickstream data	91.03% F1 score with minimal info	No cost analysis

		LR, LSTM			
Lin et al. [28]	2023	HGBDT, RF, XGB, LR	33.3M clicks	0.9031 F1 score	Scale too large for startups
Frazier et al. [29]	2022	RF, GBDT, AdaBoost	Clickstream logs	86% accuracy	High tuning time
Hendriksen et al. [30]	2020	Not Specified	Session history	96.20% F1 score	Ignored anonymity factor
Shi [31]	2021	RF, DT, LR	Online purchase data	87.5% accuracy	Lacks scale details
Satu et al. [32]	2023	Random Forest	Collected dataset	92.39% accuracy	No latency data
Necula [33]	2023	RF, DT, LR, SVM	12,330 sessions	89.73% accuracy	Complex tuning required
Abdullhadi et al. [34]	2024	XGBoost, RF, KNN	Search/Purchase data	Timeaware forecasting	Advanced data requirements
Zheng [35]	2024	DT, Random Forest	Streamlined features	Reduced memory usage	No specific metrics
Liu et al. [36]	2024	RF, XGB, RNN, LSTM	33M records	72–75% accuracy	High deep learning focus
Kim et al. [37]	2023	Not Specified	Browsing patterns	Real-time pattern integration	Lacks numeric results
Demir et al. [38]	2023	RF, XGB, MLP, LR	Various datasets	60–98% accuracy range	High infrastructure needs
Our Work					

The literature on lightweight purchase prediction models has a few limitations which are significant, limiting the practical application of such models to startups and small business enterprises in e-commerce. To begin with, despite the numerous studies asserting to support real-time, or online, prediction, they seldom report hard-end-to-end latency results, in terms of sub-100 ms inference, thus it is challenging to assess whether these models can support high-traffic settings without latencies. Second, the majority of the research is based on very large datasets that are acquired on existing platforms via millions of user records, which restricts the external validity of those models to new startups that often have very limited history. Cold-start experiments with small training data (i.e. less than 5 000 sessions) are yet to be found. Third, the existing literature primarily focuses on such predictive measures as accuracy and F1-score and neglects practical aspects like the training cost, inference memory cost, hardware dependence, and the overall computing costs. Such omissions cause startup founders to have a hard time estimating the reality of implementing such systems and its associated costs. Thus, to fill these gaps, the current work suggests a lightweight and costeffective real-time purchase prediction framework that is specifically tailored to the small ecommerce companies that work with limited datasets and limited computing capabilities and is also concerned with the practical aspects of deployment, such as the latency, resource consumption, and scalability.

3. PROPOSED METHODOLOGY:

Light Predict is a simple system to help small e-commerce startups that do not have a large amount of data or computing power make real-time predictions about their customers. Figure 1 shows how the system works: it collects information about how users interact with the website and uses this information to make automatic business decisions.

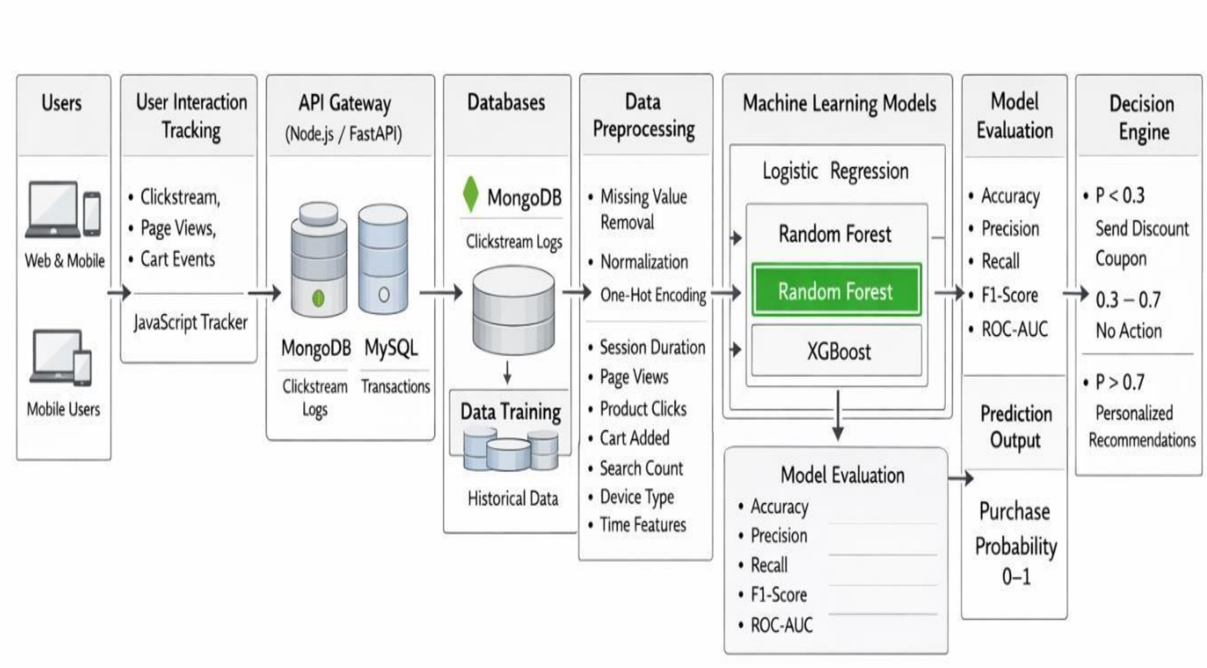

Figure 1: Lightweight Real-Time Customer Churn Prediction Framework for ECommerce Startups

3.1 System Architecture Overview:

System architecture consists of eight modules that execute three primary objectives namely easy deployment, low data requirements and efficient computation. This framework can be easily applied in small businesses of e-commerce with minimal technical capabilities.

3.2 Module Description

3.2.1 User Interaction:

A lightweight JavaScript tracker captures real time user actions including clicks, page views, session duration, scroll depth and activity in the shopping cart. The tracker is an asynchronous one such that it will not influence the performance of the site.

3.2.2 Data Collection Module:

The recorded data will be uploaded to a backend that is backed by Node.js and FastApi and stored in a hybrid database solution:

• MongoDB to store event logs that are loose. MySQL- Based session categorisation and data storage.

This has been integrated in order to make it scalable as well as having low infrastructure costs.

3.2.3 Data Preprocessing Module:

Raw data is processed through three basic necessary steps (preprocessing):

• Min-max normalisation of numerical characteristics.

• One-hot encoding of categorical variables.

The steps are used to guarantee the quality of the data, as well as to prepare the data to train the model.

3.2.4 Feature Engineering Module:

One of such representations is in Table 2, which contains about 20- 25 session-level features extracted out of the post-processed interaction data. These features are categorised into different group of behaviour to illustrate various behaviour features of the users.

Table 2: Session - Level Features

Category	Key Features
Session Metrics	Duration, Page Views, Bounce Rate
Engagement	Click Rate, Scroll Depth, Time on Product Page
Cart Behavior	Items Added to Cart, Abandoned Cart, Cart Value
User History	Previous Visits, Past Purchases
Temporal Patterns	Hour of the Day, Day of the Week, Weekend Activity
Context	Device Type, Traffic Source

Previous research has shown that these behavioral features are useful indicators for predicting customer purchase intention.

3.2.5 Machine Learning Model:

The Random Forest algorithm is the main machine learning model used in this study to predict purchase intent. There are many reasons to choose this model.

First, Random Forest models have strong performance on behavioral datasets. Previous research indicates that an accuracy rate of roughly 85–90% can be achieved with around 1,500–2,000 training sessions. So, it can be concluded that Random Forest can work efficiently on small data sets.

Second, it is possible to make predictions very quickly. This means that the model can help people make decisions almost in real time, with a prediction time of less than 100 milliseconds.

Another aspect of this model is that it does not need special hardware. It can run on a regular server with 2 vCPUs, which makes it easy for new businesses with few computing resources to use.

Random Forest also gives feature importance scores, which help business owners see how different user behaviors affect buying decisions. In addition, the ensemble learning method also lowers the chance of overfitting when using smaller datasets. For startups with very little data (fewer than 1,500 sessions), transfer learning using publicly available datasets could be a beneficial idea for future work**.**

3.2.6 Threshold Decision Engine:

Once a prediction has been made the machine learning model provides a probability score (P) that the purchase will take place (P) or not (P). This number will give how likely it is, that a user will make a purchase during the session. The probability score is forwarded to the decision engine that uses pre-established thresholds to obtain and thus decide the correct course of business action.

Table 3: Presents the mapping between probability ranges and the corresponding strategic actions

Probability Range	**Business Action**	**Strategic Objective**
$P < 0.3$	10% Discount Coupon	Convert price-sensitive users
$0.3 \leq P \leq 0.7$	No Action	Allow natural browsing
$P > 0.7$	Personalized Product Recommendations	Increase order value

3.2.7 Automated Intervention Module:

The interface of the site displays the users as they occur. As an example, the appearance of discount coupons could be in the form of simple pop up messages and product suggestions could appear in a scrolling bar of the page which displays the products. These are what make the user make a decision to purchase something. Every move that the system performs are recorded and stored to be viewed in the future and utilised to improve the model and recreate it once more.

3.2.8 Admin Dashboard:

The system also has a simple dashboard that business owners can use to keep an eye on how wellworks. The dashboard displays key information like:

- Sessions of active users right now.
- The chances of buying something
- The overall rate of conversion How well the actions shown to users work
- Statistics on how well the model works Even if business owners don't know a lot about technology, this dashboard helps them understand how users act and make better business decisions.

3.3 Deployment and Cost Analysis: LightPredict framework will be compatible with low-cost cloud infrastructure and, therefore, it will suit startups. The estimation of costs is provided in Table 4:

Table 4: System Components, Specifications, and Monthly Cost Breakdown

Component	Specification	Estimated Monthly Cost
Compute	2 vCPU, 4GB RAM	₹500–800
Storage	20GB SSD	₹100–200
Database	MongoDB Atlas Free Tier + MySQL	₹0–500
Total	—	₹600–1,500

Table 5: Comparative Analysis with Existing Approaches

Feature	Traditional ML Systems	Enterprise Deep Learning	LightPredict
Minimum Data Required	10,000+ sessions	100,000+ sessions	1,500–2,000 sessions
Infrastructure Cost	₹2,000–3,000/month	₹10,000+/month	₹600–1,500/month
Deployment Time	2–4 weeks	2–3 months	1–2 days
GPU Requirement	No	Yes	No
Model Interpretability	Medium	Low	High
Real-time Capability	Limited	Yes	Yes (<100 ms)

4. VALIDATION FRAMEWORK:

The current research is focused on LightPredict architectural framework design; its empirical validation is to be done later. In detail, this section explains the proposed validation framework and will test the effectiveness of the framework.

4.1 Dataset:

The framework would be tested using the UCI Online Shoppers Purchasing Intention Dataset that contains 12,330 user sessions and 18 behavioural measures such as page views, bounce rates, product interactions, cart activity and duration of a session. The dataset would be sampled randomly to approximate 1,500-2,000 sessions to simulate the issues that lack the scale of big startups but maintain the balance of the classes with stratified sampling.

4.2 Evaluation Metrics:

The proposed framework would be assessed using:

Table 6 : Model Evaluation Criteria and Metrics

Category	Metrics	Description
Predictive Performance	Accuracy, Precision, Recall, F1-Score, ROC-AUC	Measures how well the model predicts correct outcomes.
System Performance	Inference latency (ms), Memory usage (MB)	Evaluates computational efficiency and system resource usage.
Business Impact	Conversion lift analysis, ROI estimation	Measures the business value and financial benefit of the model.

4.3 Baseline Models:

Three baseline models would be compared to performance:

• Linear Regression (simplest interpretation of linear relationships) using only 3 independent variables (such as X 1, X 2, X 3).

The standard of accuracy of gradient boosting methods: XGBoost. Simplest deep learning: neural Network (with 2 -3 hidden layers and feeds forward)

4.4 Validation Protocol:

The validation would follow a rigorous protocol:

- Data Partitioning: 80-20 train-test split with stratification
- Cross-Validation: 5-fold cross-validation for model stability
- Threshold Optimization: A/B testing to determine optimal configurable thresholds
- Hyperparameter Tuning: Grid search for optimal parameters

4.5 Success Criteria:

The framework would be considered successful if it meets:

- Target Predictive Performance: Expected to fall within the 80-90% accuracy range based on prior literature [1][4][16]
- Inference Latency: <100 ms (suitable for real-time applications)
- Memory Footprint: <500 MB
- Deployment Cost: Approximately < ₹2,000 per month

5. EXPECTED RESULTS:

Based on literature analysis [1][4][16] and the architectural design of LightPredict, the framework is expected to demonstrate strong performance across predictive, system, and business metrics**.**

5.1 Comparative Performance Analysis:

Table 7: Supported Model and Expected Accuracy Variation

Model	Expected Accuracy Range	Supporting Sources
Random Forest (LightPredict)	80–90% (expected)	[1], [4], [16]
Logistic Regression	75–82%	[1], [7]
XGBoost	85–93%	[12], [16]
Neural Network (2–3 layer MLP)	70–85%	[17]

Variations in feature engineering techniques, dataset characteristics, and hyperparameter configurations documented in the literature are reflected in the variation in expected accuracy.

5.2 System Efficiency:

- Inference Latency: Should be able to make predictions on real-time with a latency of less than 100 ms [8].
- Memory Usage: It is expected to be 300-500 MB [12].
- Training Efficiency: If the dataset size is moderate, is expected to be computationally lightweight.

5.3 Business Impact:

Table 8: Expected Business Outcomes of the Proposed System

Business Metric	Expected Outcome
Conversion Rate	Potential improvement through targeted discount offers for low-intent users

Average Order Value	Potential increase via personalized recommendations for high-intent users
Customer Retention	Improved through timely interventions and reduced cart abandonment
Return on Investment	Expected to be favorable due to low infrastructure costs (approximately ₹600-1,500/month)

6. CONCLUSION AND FUTURE WORK:

This paper proposed the lightweight real-time purchase prediction framework and targeted at small e-commerce startups having limited data and resources. The reason why the Random Forest model is chosen is because it produces high accuracy (around 80-90) but overfitting is minimized using few key features (approximately 20-25) on small data. Currently, the system remains in the conceptual design stage, and full implementation is planned as future work. In addition, prediction accuracy may be limited when extremely small datasets are available.

Future work will focus on:

- Implementing a proof-of-concept prototype
- Testing the framework using public e-commerce datasets
- Conducting pilot studies with startup partners
- Integrating A/B testing for strategy optimization
- Extending the system to other domains such as SaaS platforms and educational technology services

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