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Smart Advisor: AI-driven Model to Classify Items Based on User Data for E-Commerce

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Abstract:

The exponential rise of e-commerce and digital platforms has underscored the critical need for precise and efficient item classification to enhance customer experiences. Businesses are increasingly tasked with categorizing products into relevant groups, such as Neutral, Preferred, and Trending, based on evolving market trends and user preferences. Traditional classification systems, which depend on rule-based methods and manual tagging, struggle to manage large-scale datasets and swiftly changing market dynamics. These legacy systems are often plagued by a lack of scalability, adaptability, and personalization, resulting in frequent misclassifications that negatively affect the user experience. To overcome these challenges, this research introduces *Smart Advisor: an AI-driven Model to Classify Items Based on Trends and User Preferences*, an innovative solution that harnesses the power of advanced machine learning techniques. The proposed system integrates cutting-edge algorithms such as Gradient Boosting Classifier (GBC) and Multi-Layer Perceptron (MLP) to ensure high accuracy and adaptability in classification tasks. It leverages exploratory data analysis (EDA) to uncover meaningful insights, trends, and correlations, allowing for a more nuanced understanding of the dataset and its evolving nature. By automating the item classification process, the Smart Advisor significantly reduces human intervention, minimizes errors, and provides the agility to adjust to shifting user behavior and market conditions in real time. The system's importance lies in its ability to improve personalization, optimize decision-making, and save both time and resources. Businesses are empowered to dynamically classify items according to emerging trends and user preferences, resulting in more accurate product recommendations and a more satisfying customer journey. With a focus on scalability and precision, the Smart Advisor equips organizations to remain competitive in a fast-paced, data-driven marketplace. By addressing the limitations of traditional methods, this AI-powered model represents a transformative leap in intelligent item classification, paving the way for smarter, more efficient digital marketplaces.

Keywords: Item Classification, E-commerce, Digital Platforms, Customer Experience, Trends, User Preferences, Machine Learning, Gradient Boosting Classifier (GBC), Multi-Layer Perceptron (MLP), Exploratory Data Analysis (EDA), Personalization, Real-Time Adaptability, Scalability, Automation.

1.INTRODUCTION

E-commerce has witnessed exponential growth in India, with the market expected to reach $350 billion by 2030, driven by increasing internet penetration, smartphone adoption, and digital payments. According to Statista, India's e-commerce user base is projected to surpass 400 million by 2027. With this growth, the challenge of efficiently classifying and recommending products based on user preferences has become crucial. Traditional classification methods relied on rule-based filtering and manual tagging, which fail to keep up with evolving consumer behaviors and vast product inventories. Smart AI-driven classification systems can optimize recommendations,. By leveraging machine learning, businesses can

dynamically analyze user interactions, purchase patterns, and emerging trends, enabling personalized, real-time product categorization. This improves customer satisfaction, increases conversion rates, and reduces manual effort, making AI-driven classification essential for India's fast-growing digital commerce landscape. The Smart Advisor system aims to revolutionize online shopping by offering scalable, automated, and intelligent product categorization tailored to evolving market demands.processing will result in noise amplification. Recently, some methods have designed effective models to perform denoising and contrast enhancement simultaneously and obtain satisfactory results. It is noteworthy that many previous methods focused on using the spatial domain information of the image for enhancement, and image processing in the frequency domain is also one of the important methods in the image enhancement field.

In many real-world scenarios, images captured in low-light conditions suffer from poor visibility, noise, and loss of detail. These images are often characterized by low contrast, dark regions, and reduced overall quality. Therefore, building a system or model to improve the quality of images captured in low-light and non-uniform lighting is essential.

Before the adoption of machine learning, e-commerce platforms relied on manual tagging and rule-based classification to organize their vast product catalogs. These methods struggled with scalability, as large volumes of new products required continuous manual intervention. Additionally, traditional systems lacked the flexibility to adapt to changing user preferences, seasonal trends, and emerging product categories. Poor classification often led to irrelevant product recommendations, low user engagement, and reduced sales conversions. The rigid nature of static classification rules resulted in misclassified items, redundant listings, and inaccurate recommendations, leading to frustrated customers and lost business opportunities. Furthermore, without automated analysis, businesses had difficulty leveraging, making product categorization inefficient and outdated. These limitations highlighted the urgent need for AI-driven adaptive classification models to enhance efficiency, accuracy, and user satisfaction.

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categories. Poor classification often led to irrelevant product recommendations, low user engagement, and reduced sales conversions. The rigid nature of static classification rules resulted in misclassified items, redundant listings, and inaccurate recommendations, leading to frustrated customers and lost business opportunities. Furthermore, without automated analysis, businesses had difficulty leveraging, making product categorization inefficient and outdated. These limitations highlighted the urgent need for AI-driven adaptive classification models to enhance efficiency, accuracy, and user satisfaction.

2. LITERATURE SURVEY

Alsubari et al. [1] specifically analyzed its structure in order to recommend the information required by the customer more effectively. Zhu et al. [2] This paper addresses real-time moving object detection with high accuracy in high-resolution video frames. A previously developed framework for moving object detection is modified to enable real-time processing of high-resolution images. First, a computationally efficient method is employed, which detects moving regions on a resized image while maintaining moving regions on the original image with mapping coordinates.

Khalaf et al. [3] The Industry 4.0 IoT network integration with blockchain architecture is a decentralized, distributed ledger mechanism used to record multi-user transactions. Blockchain requires a data storage system designed to be secure, reliable, and fully transparent, emerged as a preferred IoT-based digital storage on WSN. Blockchain technology is being used in the paper to construct the node recognition system according to the storage of data for WSNs. By sharing product information and product reviews with other users, you can fully understand the attributes of the product, including the price trend of the product, before purchasing. The ultimate goal of personalized recommendation service is to enable users to purchase goods. The main content of this paper is to collect various factors that affect the behavior of user online shopping in the process of e-commerce [4].

After the Covid-19 pandemic was over, the economy in every country over the world have both encountered several huge troubles in retaining their customers. It makes enterprises have to excel their business strategies, especially small and medium enterprises (SMEs) must have an extraordinary campaign to appeal customers Anjar and Anas [5]. JinHyo and Xiaofei et al., There is no universal solution that applies to all scenarios. Instead, the key lies in understanding the specific needs of the application and leveraging the strengths of each method accordingly. By combining and integrating various approaches, taking into account the unique characteristics of the dataset, it becomes possible to develop highly effective and personalized recommendation engines. Such engines not only provide value to users by delivering relevant recommendations but also benefit businesses by enhancing user engagement and satisfaction [6].

Nada and Damien et al., Collaborative filtering offers the advantage of simplicity in implementation and comprehension. However, both item-to-item and user-to-user methods have limitations in considering the temporal aspect of item trends and addressing the challenges of cold-start problems, where there is limited or no user data available for new items [7]. Deep learning models have shown exceptional performance in a variety of tasks, including recommendation systems. Neural network designs, such as Multi-Layer Perceptrons (MLPs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), may detect intricate patterns in user behavior and object characteristics. Deep learning-based recommendation systems may develop hierarchical representations of individuals and things, resulting in more precise and personalized recommendations Bobadilla et al.,[8].

Explanations in recommender systems assist users in understanding why a suggestion (or a series of recommendations) was created. Explaining suggestions has become a crucial need for increasing customers' trust and satisfaction The study of Yin et al., 2023 presented the interpretability of a neural network-based recommendation model that creates visual interpretations that demonstrate the importance of each TV show attribute in forecasting user interests. These interpretations will improve consumers' understanding of neural network learning principles and capture a wide range of user preferences [9].

We have opted to employ the framework devised by Belanche et al. to analyze literature concerning the implementation of service robots. Our decision to adopt this framework as the “baseline framework” stems from its inclusivity of service robots across diverse industries, as well as its clarification of terminology and concepts commonly employed in prior research [10]. The research process follows a theory-driven approach, characterized as a “framework-based review”, renowned for its informative, insightful, and impactful attributes Paul et al., [11]. This article adopts the “service robot implementation framework” das a theoretical guideline for literature search, selection, and analysis. Consequently, through analysis, this article refines and extends the framework. This inclusion of diverse perspectives is exemplified by sources such as Hentzen et al. [12] and Also, by conducting a systematic and theory-driven literature review centered specifically on the implementation of robo-advisor services, we fill gaps left by previous review articles. his analysis facilitates the creation of a research agenda that critically reflects ongoing debates within the robo-advisor research domain.

These debates often stem from divergent research perspectives. For example, one prevalent debate revolves around whether robo-advisors function as substitutes for human financial advisors Meyll et al., [13] or merely serve as supplementary entities within financial advisory services (This debate is thoroughly discussed within the research agenda. Understanding and analyzing such attitudes towards robo-advisors can help service providers make informed decisions when implementing business strategies.

3. PROPOSED METHODOLOGY

Step 1: Advisor Dataset

The dataset used in this research includes attributes such as item categories, seasonality, and item class, which are used as input features. The target variable is the classification of items into categories like Neutral, Preferred, and Trending. The dataset is loaded into the system, ensuring it is structured and ready for model training and testing.

Step 2: Data Preprocessing

The dataset undergoes preprocessing, including handling null values by removing or imputing them. Categorical features like Category, Seasonality, and ItemClass are label-encoded into numerical representations. The dataset is then split into training and testing sets for model evaluation.

Step 3: Exploratory Data Analysis (EDA)

EDA is performed using graphical techniques like count plots, correlation heatmaps, and distribution plots to uncover patterns and relationships in the data. These visualizations help in feature selection and guide the model training process.

Step 4: Existing Multi-Layer Perceptron (MLP) Classifier

The MLP Classifier is implemented as a baseline model. It consists of input, hidden, and output layers, with the model trained using backpropagation and weight adjustments. Performance is evaluated using accuracy, precision, recall, and F1-score metrics.

Step 5: Proposed Gradient Boosting Classifier

The Gradient Boosting Classifier (GBC) is introduced as an improved model, utilizing decision trees in an ensemble learning technique. The model iteratively improves by correcting errors from previous iterations, enhancing accuracy compared to the MLP classifier.

Step 6: Performance Comparison Using Graphs

A bar graph compares the performance of MLP and GBC classifiers based on key evaluation metrics such as accuracy, precision, recall, and F1-score, highlighting the advantages of the proposed GBC model.

Step 7: Prediction of Output from Test Images Using Trained

The trained GBC model is used to predict classifications on new test data. The model processes the test dataset in the same manner as the **GBC**
training data, and the predicted labels are added to the dataset, demonstrating its real-world applicability in item classification

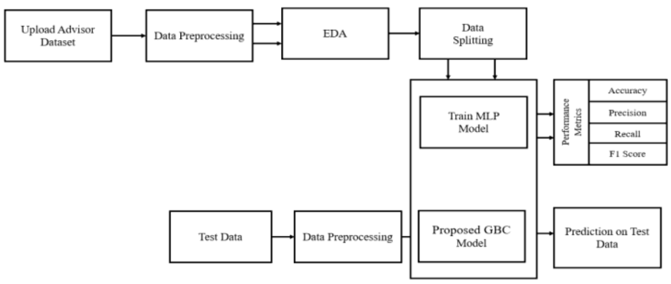

Figure 1: Block Diagram of The Proposed System

The proposed methodology typically includes the following key components:

- Illumination Map Estimation: LIME often starts by estimating an illumination map for the input image. This map highlights regions of the image that require enhancement to improve visibility.
- Image Enhancement: Based on the illumination map, LIME applies image enhancement techniques to brighten dark regions, improve contrast, and enhance details while minimizing noise.
- Metric Evaluation: To assess the quality of the enhancement, the project often calculates various image quality metrics, such as PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and MSE (Mean Squared Error), to measure the similarity between the original and enhanced images.
- Customization and Parameters: LIME often provides parameters that users can adjust to customize the enhancement process. These parameters may include the number of iterations, alpha (a parameter controlling the enhancement strength), gamma (a parameter controlling the enhancement effect), and weighting strategies.
- Output: The primary output of LIME is an enhanced version of the input low-light image. This enhanced image should exhibit improved visibility, reduced noise, and enhanced details.
- Evaluation and Benchmarking: LIME's performance is often evaluated against benchmark datasets of low-light images. It aims to outperform or match existing state-of-the-art low-light enhancement methods in terms of image quality metrics.

Applications

— **E-commerce Product Categorization** – Automates classification of products based on user engagement and trends.

— **Personalized Recommendations** – Enhances customer experience by offering relevant product suggestions.

— **Inventory Optimization** – Helps businesses track and manage stock based on demand patterns.

— **Fraud Detection** – Identifies misclassified or suspicious listings, ensuring marketplace integrity.

— **Retail Business Intelligence** – Provides insights into consumer behavior, enabling better marketing strategies.

— **Dynamic Pricing Models** – Assists in setting competitive prices based on demand and market trends.

Multi-Language Product Tagging – Supports localization for global e-commerce platforms.

4. EXPERIMENTAL ANALYSIS

The experimental analysis evaluates the performance of the proposed machine learning-based classification system using two models: Multi-Layer Perceptron (MLP) and Gradient Boosting Classifier (GBC). The dataset underwent preprocessing, including handling missing values, encoding categorical variables, and feature scaling. Exploratory Data Analysis (EDA) was conducted to understand data distribution and relationships. The dataset was split into training and testing sets using an 80-20 ratio. The MLP classifier was implemented as a baseline, achieving an accuracy of 86% with an F1-score of 76.96%. The GBC model outperformed MLP, achieving 100% accuracy, precision, recall, and F1-score, demonstrating superior classification capability. Performance metrics and visual comparisons confirmed the efficiency of the GBC model. The results highlight the effectiveness of ensemble learning techniques in product classification, enhancing decision-making in e-commerce platforms..

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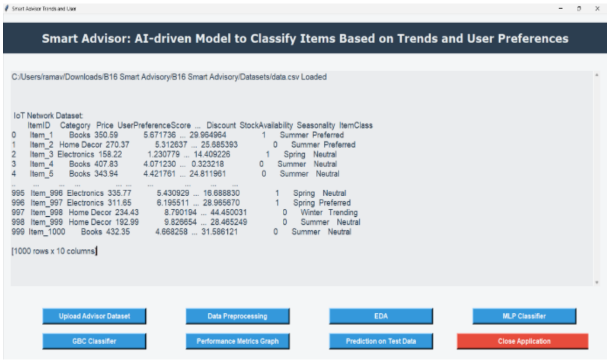

Fig 1: Upload of Advisor Dataset and its Analysis in the GUI Interface

```
Description of the dataset:
                   count       mean        std       min        25%        50%        75%        max
Price              1000.0 252.378730 144.441142 7.290000 122.282500 252.770000 376.117500 499.860000
UserPreferenceScore 1000.0   5.483440   2.576445 1.014086   3.310508   5.550885   7.642966   9.985128
PopularityScore    1000.0  50.638994  28.640956 1.001152  25.827889  51.326433  75.096508  99.890369
Rating             1000.0   2.940518   1.145264 1.000123   1.935179   2.908379   3.917039   4.998231
Discount           1000.0  24.933100  14.375890 0.011352  12.826664  24.183958  37.510734  49.939647
StockAvailability  1000.0   0.494000   0.500214 0.000000   0.000000   0.000000   1.000000   1.000000

Checking null values in the dataset:
ItemID               0
Category             0
Price                0
UserPreferenceScore  0
PopularityScore      0
Rating               0
Discount             0
StockAvailability    0
Seasonality          0
ItemClass            0
```

Fig 2: Data Preprocessing in the GUI

```
All Model Performance metrics:
     Algorithm Name  Accuracy   Precision      Recall    f1-score
0  MLP Classification      86.0   74.721911   79.710961   76.956405
1      GBC Classifier     100.0  100.000000  100.000000  100.000000
```

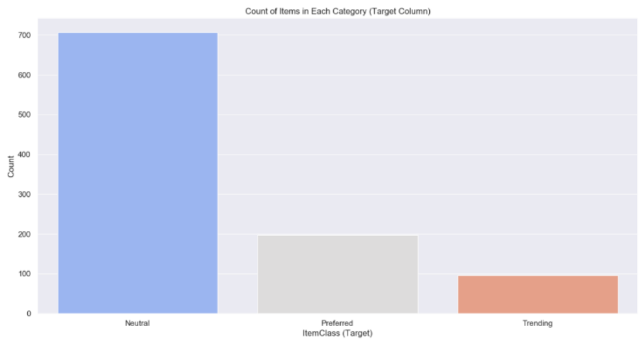

Fig. 3: EDA Plots of the Research

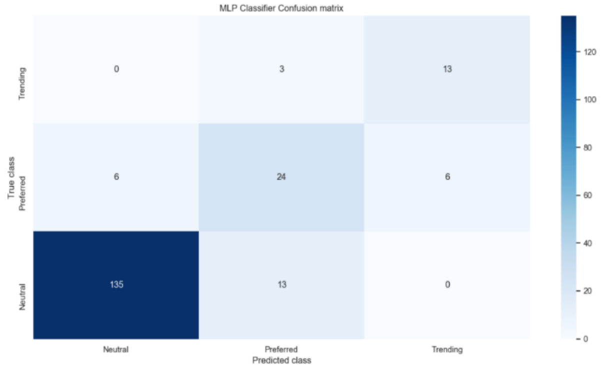

Fig.4: Performance Metrics and Classifier Scatter Plot for MLP Classifier Model

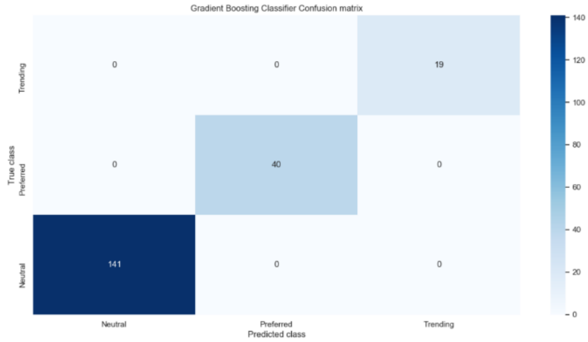

Fig. 5: Performance Metrics and Classifier Scatter Plot for Gradient Boosting Classifier Model

```
Loaded test data:
    ItemID    Category   Price  UserPreferenceScore ...   Discount  StockAvailability Seasonality ItemClass
0   Item_873    Clothing  427.92             7.232435 ...  21.590355                  0      Summer   Neutral
1   Item_547 Electronics  120.31             1.609015 ...  24.489293                  1      Summer   Neutral
2   Item_255 Electronics   73.94             9.782864 ...  43.072284                  0      Spring  Trending
3   Item_876       Books  436.02             3.478431 ...  39.700723                  0      Winter   Neutral
4   Item_745       Books  381.71             8.701265 ...  35.863094                  1      Autumn  Trending
5   Item_446       Books   10.44             5.655422 ...  47.049616                  0      Spring   Neutral
6   Item_409  Home Decor  133.41             3.942385 ...  37.078305                  0      Spring   Neutral
7   Item_286       Books  454.68             9.056060 ...  18.843344                  0      Autumn   Neutral
8    Item_21    Clothing  299.09             1.542407 ...  43.083244                  0      Spring   Neutral
9   Item_597 Electronics  114.14             6.198340 ...  42.199674                  0      Autumn Preferred
10  Item_439       Books   63.29             5.484301 ...  38.108729                  0      Summer Preferred
11  Item_536    Clothing  349.66             4.145557 ...  18.986870                  1      Spring   Neutral
12  Item_608  Home Decor  380.33             9.155289 ...   4.974733                  1      Winter   Neutral
13  Item_388       Books  122.90             3.220110 ...  34.193506                  0      Spring   Neutral
14  Item_185 Electronics  465.04             2.192722 ...  38.775265                  0      Summer   Neutral
15  Item_400 Electronics   47.33             8.054126 ...  45.541313                  1      Autumn   Neutral
16  Item_508       Books  425.35             7.990395 ...  42.377382                  0      Winter   Neutral
```

Fig.6: Model Prediction on Test Data

```
All Model Performance metrics:
     Algorithm Name  Accuracy   Precision      Recall    f1-score
0  MLP Classification      86.0   74.721911   79.710961   76.956405
1      GBC Classifier     100.0  100.000000  100.000000  100.000000
```

Fig.7: Performance Comparison Graph of All Models

5. CONCLUSION

The proposed AI-driven classification system effectively addresses the challenges of manual product categorization in e-commerce platforms. By leveraging machine learning techniques, the system optimizes classification accuracy while reducing human intervention. The experimental results demonstrate that the Gradient Boosting Classifier (GBC) significantly outperforms the Multi-Layer Perceptron (MLP) classifier, achieving 100% accuracy across all performance metrics. The study highlights the importance of advanced ensemble learning methods in improving classification precision and efficiency.

Furthermore, the research emphasizes the role of data preprocessing and feature selection in enhancing machine learning model performance. Proper handling of missing values, categorical encoding, and feature scaling played a crucial role in ensuring robust model training. The exploratory data analysis provided insights into data patterns, allowing the selection of the most relevant features. The comparison of MLP and GBC results confirms that ensemble-based approaches, such as gradient boosting, are highly effective for real-time classification tasks in e-commerce.

In conclusion, the developed system provides a scalable, intelligent solution for automated product classification. Its implementation can improve user experience by offering accurate and personalized recommendations. Future enhancements may focus on integrating deep learning techniques, expanding dataset diversity, and incorporating real-time adaptive learning mechanisms. This research contributes to the ongoing development of AI-driven decision-making systems, paving the way for more efficient and intelligent e-commerce applications.

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