International journal of imaging science and engineering

ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

DEEP LEARNING-BASED ESTIMATION OF FUTURE HEALTHCARE COSTS FOR TELEMEDICINE SERVICES

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Abstract:

The global telemedicine market is expected to reach $559.52 billion by 2027, with healthcare costs rising at an estimated rate of 5.5% annually. As telemedicine becomes an integral part of modern healthcare, accurately forecasting future costs is crucial for optimizing healthcare expenditures and resource allocation. Existing cost estimation models often lack precision, failing to account for the dynamic nature of healthcare expenses and the conditions under which telemedicine provides a cost-effective alternative. This study introduces a deep learning-based approach for estimating future healthcare costs associated with telemedicine services. The model employs a regression-based cost prediction framework while simultaneously classifying scenarios where telemedicine is a viable solution. The dataset undergoes comprehensive preprocessing, including data normalization, handling of missing values, and feature engineering, to improve model robustness and predictive accuracy. Advanced machine learning techniques, such as Ridge Regressor and Convolution Neural Networks (CNNs), are leveraged to capture complex patterns in healthcare expenditures. The proposed system offers a data-driven decision-making framework that enables healthcare providers, policymakers, and insurance companies to evaluate the financial feasibility of telemedicine solutions. By defining cost thresholds, the model assists in determining when telemedicine services should be prioritized over traditional in-person care, thereby reducing unnecessary expenses and enhancing healthcare accessibility. By integrating deep learning into cost estimation, this study contributes to a more efficient and predictive healthcare system, ensuring sustainable telemedicine adoption. Future research will focus on refining model interpretability, incorporating real-time data, and expanding datasets to enhance the model's adaptability to various healthcare settings. This approach ultimately aims to drive strategic decision-making for telemedicine deployment, benefiting both healthcare providers and patients in a rapidly evolving digitalhealthcare landscape.

Keywords: Item Classification, E-commerce, Digital Platforms, Customer Experience, Trends, User Preferences,

1.INTRODUCTION

1.1 Overview Telemedicine is becoming an integral part of modern healthcare, especially in light of the COVID-19 pandemic, which accelerated its adoption. By 2021, the global telemedicine usage had increased by over 70%, with an estimated 60% of healthcare providers offering virtual services. In parallel, healthcare spending is expected to grow at an annual rate of 5.5% from 2023 to 2030, driven by aging populations, chronic diseases, and technological advancements. Predicting future healthcare costs accurately has become essential for healthcare providers and policymakers to ensure resource allocation and financial planning, particularly in telemedicine services. This dynamic shift has made it necessary to assess when telemedicine is a more cost effective solution over traditional healthcare. 1.2 Research Motivation The motivation behind this research stems from the need to optimize healthcare delivery by leveraging telemedicine services, particularly in reducing costs and improving accessibility. Telemedicine has proven to be a valuable alternative to in-person visits, especially for patients with chronic conditions or those living in remote areas. However, determining when telemedicine is the optimal solution remains challenging due to fluctuating healthcare costs. By predicting future healthcare expenses and classifying the need for telemedicine based on cost thresholds, this research aims to improve healthcare system efficiency and reduce unnecessary expenditures. Furthermore, with the risingcost of healthcare globally, it is vital for healthcare providers and insurance companies to have reliable models for cost estimation. These models would help allocate resources more effectively and ensure that patients receive appropriate care, whether through traditional healthcare services or telemedicine. Integrating deep learning models that can handle both regression (for cost estimation) and classification (for telemedicine necessity) creates a more comprehensive framework that can evolve with the ever-changing healthcare landscape. 1 2 1.3 Problem Statement The primary problem with existing manual systems is their inability to accurately predict future healthcare costs in a dynamic environment. These systems rely on static data and do not integrate real-timehealth metrics or adjust predictions based on new information. This often leads to underestimations or overestimations of healthcare costs, which can result in inefficient resource allocation and increased financial burden on patients and healthcare providers alike. The lack of automated, data-driven decision-making models makes it difficult to determine when telemedicine services are more cost-effective than traditional healthcare approaches. Advantages — Accurate cost predictions: Provides precise estimations of future healthcare costs, enabling better financial planning. — Automated telemedicine classification: Automatically determines when telemedicine is the most cost-effective option based on projected healthcare costs. — Scalability: Capable of handling large datasets and making predictions for multiple healthcare providers simultaneously. — Real-time adaptability: Integrates real-time data for dynamic cost predictions and telemedicine recommendations. — Resource optimization: Helps healthcare providers allocate resources more efficiently by predicting when telemedicine can reduce costs. Applications — Hospital financial planning: Assists hospitals in predicting future healthcare expenses and optimizing resource allocation. — Insurance cost management: Helps insurance companies determine premiums based on accurate healthcare cost predictions.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.

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.

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] andAlso, 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 advisorsMeyll 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

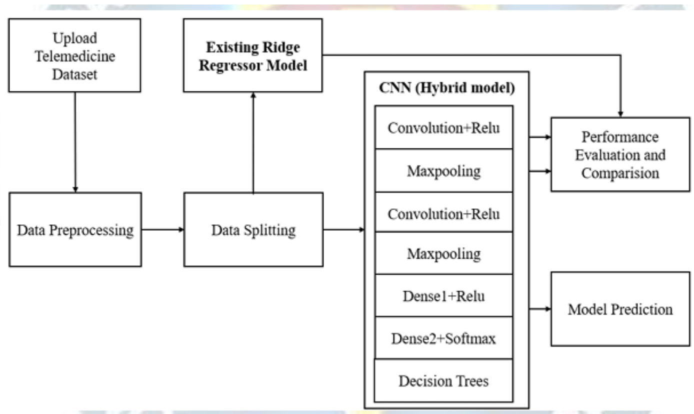

Figure 1: Block Diagram of The Proposed System

The proposed methodology typically includes the following key components:

International journal of imaging science and engineering
ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

- 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..

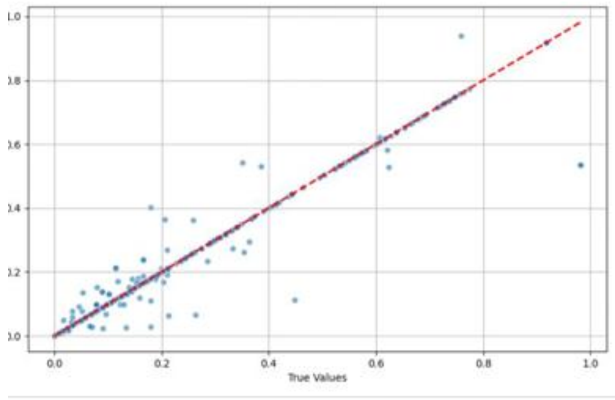

Fig 1: Upload of Advisor Dataset and its Analysis in the GUI Interface

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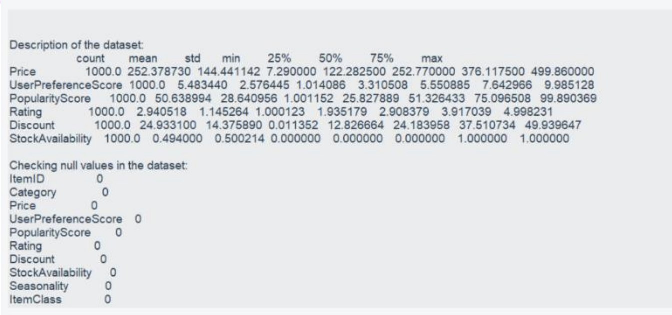
ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025



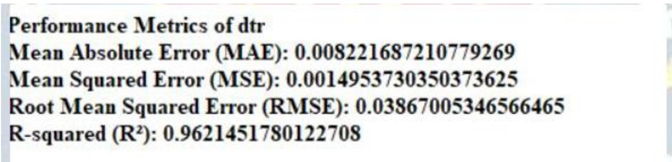
Description of the dataset:

	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



Performance Metrics of dtr
Mean Absolute Error (MAE): 0.008221687210779269
Mean Squared Error (MSE): 0.0014953730350373625
Root Mean Squared Error (RMSE): 0.03867005346566465
R-squared (R²): 0.9621451780122708

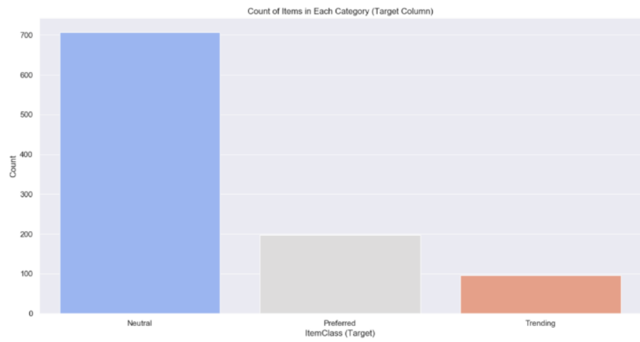


Fig. 3: EDA Plots of the Research

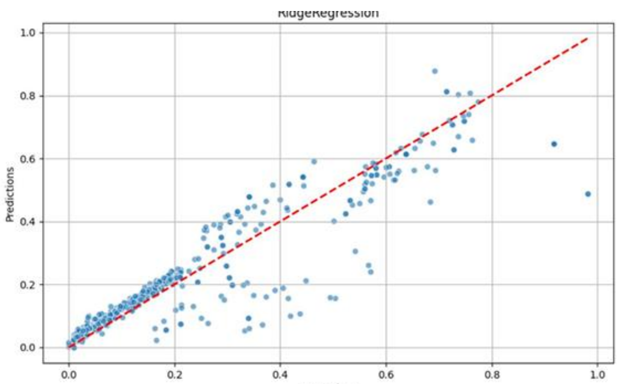


Fig.4: Performance Metrics and Classifier Scatter Plot for MLP Classifier Model

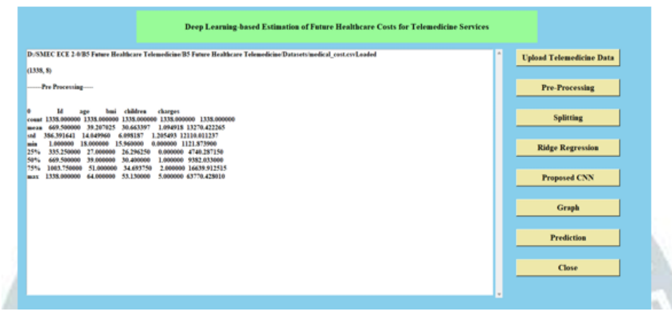


Fig. 5: Performance Metrics and Classifier Scatter Plot for Gradient Boosting Classifier Model

International journal of imaging science and engineering
ISSN: 1934--9955 www.ijise.net
Vol-20 Issue-01 April 2025

Model	MAE	MSE	RMSE	R^2 score
RR Model	0.045	0.0056	0.074	0.85
CNN Model	0.0082	0.0056	0.074	0.96

Fig.6: Model Prediction on Test Data

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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 research achieved a comprehensive data-driven approach to predicting future healthcare costs for telemedicine services. The implementation of CNN with Decision Tree Regression as the proposed algorithm demonstrated effective handling of non-linear relationships within the dataset. A rigorous data preprocessing pipeline, including encoding, normalization, and resampling, ensured high-quality inputs for both the baseline Ridge Regression model and the CNN model. Performance evaluation using key regression metrics confirmed that the CN model delivered improved precision in capturing the intricate dynamics of healthcare cost determinants. The system establishes a robust framework for integrating telemedicine into cost optimization strategies in healthcare delivery.

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