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TELECAREECONOMICS: AI-POWERED ESTIMATION OF PERSONALIZED FUTURE HEALTHCARE COSTS IN REMOTE MEDICAL 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 digital healthcare landscape.

Key words: Telemedicine, Healthcare Cost Prediction, Consultation Cost Estimation, Healthcare Economics, Digital Health Services, AI in Telemedicine

1. INTRODUCTION

Telemedicine has revolutionized healthcare delivery, offering remote consultations and continuous patient monitoring, especially during critical times like the COVID-19 pandemic. According to McKinsey & Company, telehealth usage increased 38 times from the pre-COVID-19 baseline, with around 76% of consumers expressing interest in virtual care. In the United States alone, telehealth claims rose by over 4,000% between 2019 and 2020, driven by the need for social distancing and healthcare access from home. Globally, the telemedicine market was valued at approximately USD 87.8 billion in 2022 and is projected to reach USD 286.2 billion by 2030, growing at a CAGR of 18.6%. The increased adoption of telemedicine has led to a surge in healthcare data generation, ranging from patient vitals and consultation transcripts to diagnostic records. With insurers and healthcare providers seeking to optimize budgets, forecasting future healthcare costs in telemedicine has become a priority. The cost drivers in virtual care include consultation frequency, digital infrastructure costs, follow-up diagnostics, wearable device integration, and post-consultation medication adherence. Furthermore, the variations in cost across regions, service types, and patient demographics introduce high complexity into prediction models. Forecasting future costs accurately ensures sustainable business models for providers and reduces financial uncertainty for patients and insurers. Accurate cost estimation is pivotal for managing operational expenses, government reimbursements, and insurance premium calculations. Inaccurate forecasts can lead to overburdened digital infrastructure, unplanned budget overruns, and lower service accessibility in remote regions. Thus, data-driven prediction models are increasingly

Fig 1. AI in telemedicine

becoming central to managing telemedicine services effectively. In real-time telemedicine operations, cost variations are influenced by multiple unpredictable factors such as sudden spikes in patient volumes, network latencies, device failures, and prescription patterns. Companies must analyze vast datasets from wearable devices, electronic health records, and communication logs to ensure efficient scheduling, resource allocation, and budget forecasting. The failure to incorporate predictive analytics in these environments can lead to system inefficiencies, unnecessary medical expenses, and poor patient satisfaction rates.

2. LITERATURE SURVEY

The use of artificial intelligence (AI) and machine learning (ML) in healthcare has been rapidly evolving, offering transformative possibilities for improving patient care, diagnostics, and clinical decision-making. AI and ML are often used interchangeably, but they represent distinct concepts within the broader field of computational sciences. AI is a broad category that refers to the simulation of human intelligence in machines, enabling them to perform tasks typically requiring human cognition, such as reasoning, learning, problem-solving, and decision-making. ML is a subset of AI and focuses on developing algorithms that enable computers to learn from data and improve their performance on specific tasks without being explicitly programmed [1]. In the context of healthcare, AI encompasses a wide array of technologies, including expert systems, natural language processing, and robotics, while ML specifically leverages statistical and computational techniques to analyze large datasets, identify complex patterns, and make data-driven predictions or decisions. Leveraging ML models can also allow automated learning and adaptation, which is particularly powerful in dynamic environments like healthcare [2]. These technologies have demonstrated their potential to revolutionize the way healthcare is delivered by providing data-driven insights, enhancing predictive capabilities, and assisting healthcare professionals in delivering personalized treatment [3].

Pediatric healthcare presents unique challenges compared to adult care. Children are not simply smaller versions of adults; they have distinct developmental, physiological, and psychological needs [4]. Additionally, the medical data for children are often limited due to smaller sample sizes, ethical concerns, and variability across different developmental stages [4]. ML offers promising solutions to address these challenges by improving diagnostic accuracy, enhancing treatment strategies, and predicting outcomes tailored to pediatric patients.

In recent years, healthcare costs have increased significantly [5], while physician and nursing staff shortages have become more pronounced, particularly since the COVID-19 pandemic [6]. The increasing demand for healthcare services, coupled with limited human resources, has strained the system, affected the quality of care and increasing burnout among healthcare professionals [6]. AI and ML hold significant potential to improve efficiency, enhance patient outcomes, and alleviate the work burden faced by healthcare providers. By automating routine tasks, providing predictive insights, and supporting clinical decision-making, these technologies can help reduce the workload of healthcare professionals, decrease costs, and ultimately lead to better care delivery.

In addition to identifying advances, this review also focused on uncovering gaps in the current research and discussing the challenges faced by ML applications in pediatric settings. By understanding these gaps and challenges, this review aims to provide insights into future research opportunities and the potential improvements that can be made to integrate ML effectively into pediatric healthcare.

Diagnostic support systems have become increasingly integral in pediatric care, both in inpatient and outpatient settings. While most of these systems are currently based on rule-based AI with significant false alarms, the emerging literature indicates that ML can accurately diagnose complex pediatric conditions early in the disease process by analyzing clinical and demographic data. For instance, it has been demonstrated that ML plays a role in recommending appropriate genetic testing based on phenotype data, thereby enhancing diagnostic precision [7]. Convolutional neural networks have further enhanced diagnostic accuracy for pediatric brain tumors using MRI scans, outperforming traditional diagnostic methods. This improvement facilitates earlier interventions and better patient outcomes [8].

Similarly, studies have illustrated the use of ML in monitoring disease progression, predicting disease activity and relapse, and optimizing treatment strategies for pediatric Crohn's disease patients [9]. In asthma management, ML has been used to analyze electronic health records (EHRs) and predict respiratory complications, enabling rapid interventions for high-risk children. This approach has reduced emergency department visits for asthma exacerbations, demonstrating its transformative impact on patient outcomes and healthcare efficiency [10,11]. Further expanding the scope of diagnostic support, researchers have constructed ML models that improve diagnostic accuracy for appendicitis, reducing the risk of missed or delayed diagnoses [12].

3. PROPOSED SYSTEM

The research focuses on developing a deep learning-based estimation model for future healthcare costs in telemedicine services. With the increasing adoption of telemedicine, accurately predicting healthcare expenses is crucial for optimizing resource allocation, reducing patient costs, and improving service efficiency. The model utilizes historical patient data, medical conditions, treatment patterns, and other influencing factors to forecast future healthcare costs using regression-based deep learning techniques. The proposed approach leverages Convolutional Neural Networks (CNNs) for regression to extract complex patterns and relationships from structured healthcare data. Traditional regression models, such as Ridge Regression, are also explored for benchmarking

The study begins with a comprehensive **dataset** comprising anonymized telemedicine service records from multiple healthcare providers, featuring variables such as consultation type, patient demographics, visit frequency, wearable usage, diagnostic tests, digital infrastructure, and regional healthcare costs, with the target variable being the total consultation cost per patient. Data privacy is ensured through anonymization, and synthetic data is used to balance under-represented cases. In the preprocessing phase, missing values are imputed (medians for numerics, modes for categoricals), categorical variables like region and consultation type are one-hot encoded, and numerical features (age, cost, duration) are normalized using Min-Max scaling. The dataset is then split into training, validation, and testing subsets (70:10:20 overall) using stratified sampling where needed to ensure balanced representation of cost distributions, with consistent shuffling and random seeding for reproducibility. As a baseline model, a Ridge Regressor is trained, chosen for its L2 regularization ability to manage multicollinearity (e.g., test count vs. consultation duration), though its linear nature limits its ability to model complex patterns. To address this, a hybrid CNN + DTR model is proposed, where a 1D Convolutional Neural Network is applied to tabular data (reshaped into 2D matrices), automatically learning spatial and interaction-based patterns through convolution and pooling layers. The final CNN feature vector is flattened and passed to a Decision Tree Regressor (DTR), which performs recursive splits on these deep features to predict consultation cost. This combination leverages CNN's representation power and DTR's ability to capture non-linear cost boundaries, yielding a powerful and interpretable healthcare cost prediction model

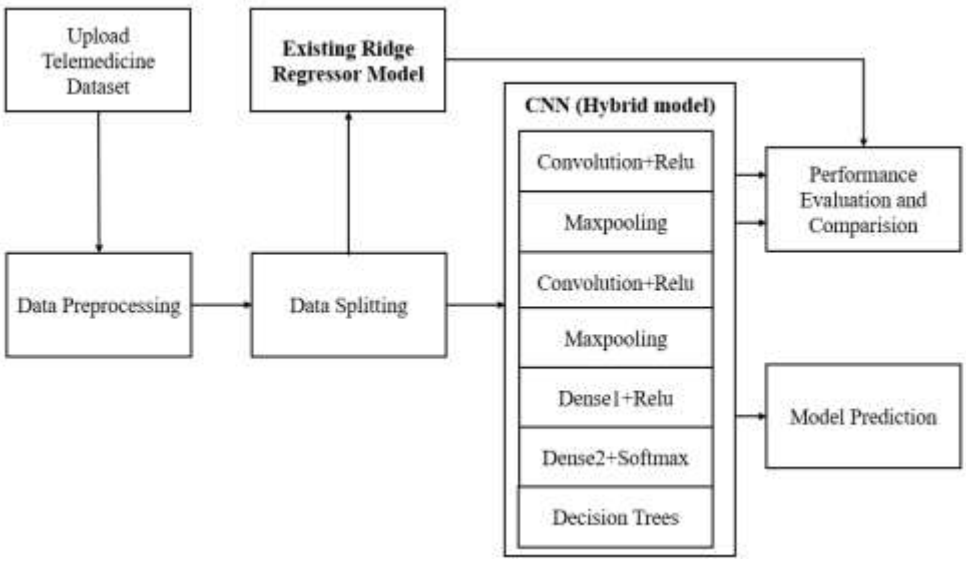

Fig 2. Architectural Block Diagram of the Proposed System.

A Convolutional Neural Network (CNN) is a deep learning model specifically designed to process spatial and grid-like data, such as images and time-series data. It excels at pattern recognition, feature extraction, and classification tasks.

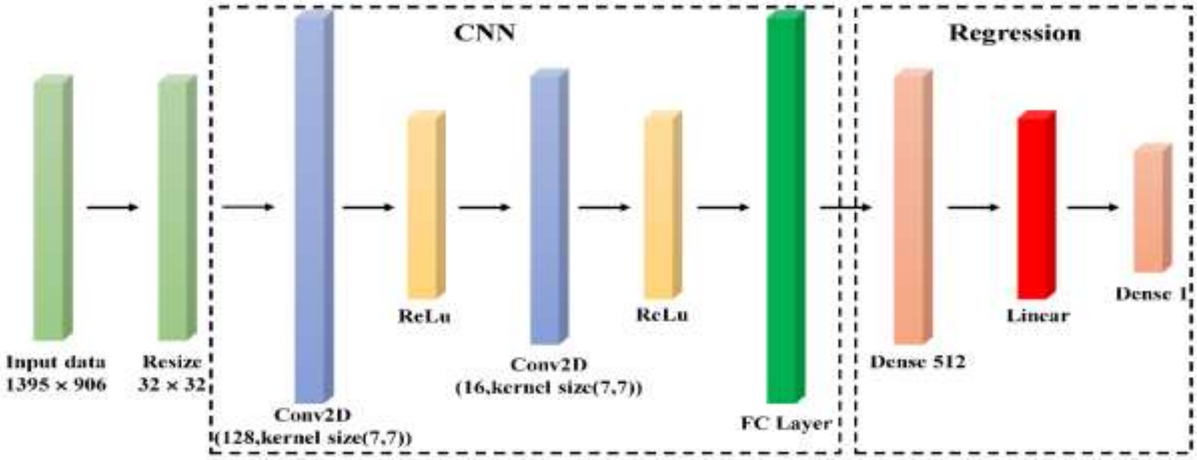

Fig 3. Proposed CNN feature extraction.

The Convolutional Neural Network (CNN) method is highly effective for applications like telemedicine cost prediction because it can automatically learn complex patterns and hierarchical features from sequential or structured input data without extensive manual feature engineering. Its architecture is well-suited to capture local dependencies and interactions within input features, making it particularly advantageous when the data exhibits spatial or temporal correlations. The ability of CNNs to reduce dimensionality via pooling layers and prevent overfitting with dropout makes this method robust and adaptable to diverse healthcare datasets, ensuring the input representation is tailored to the specific application domain.

The Decision Tree Regressor is especially advantageous in application-specific domains like telemedicine cost prediction because of its transparency, simplicity, and capability to handle both numerical and categorical data. It does not require feature scaling or transformation, making it suitable for heterogeneous healthcare data where variables such as age, region, and service type influence cost. Its ability to model non-linear relationships and interactions between features allows it to provide interpretable and data-driven decisions, which is critical in clinical environments where understanding the basis of cost estimation is essential for auditing and trust.

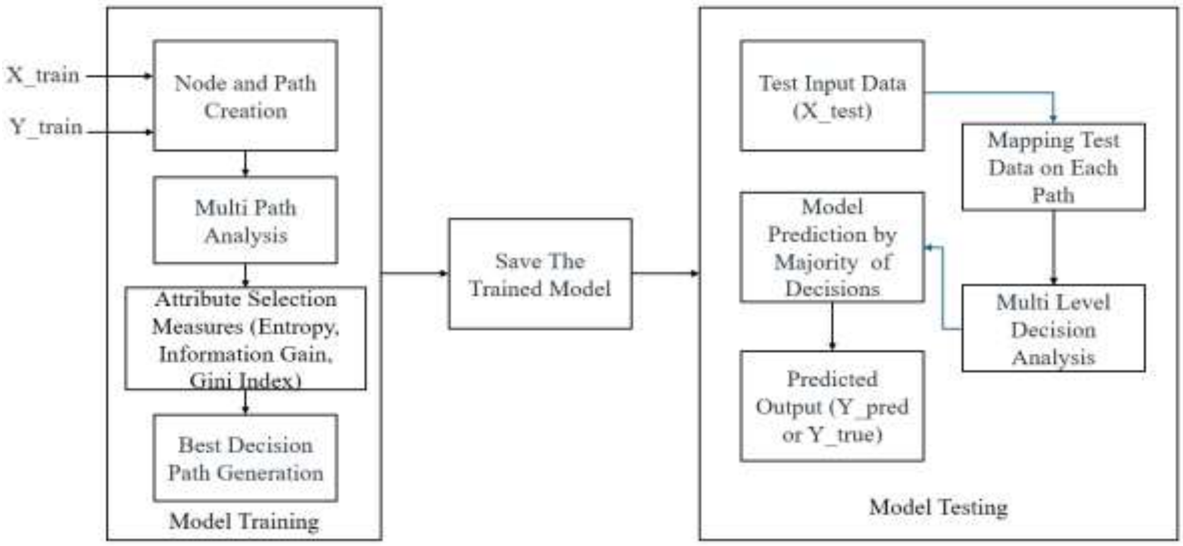

Fig 4. Proposed DTR Algorithm.

Decision Tree Regression offers several key advantages that make it a powerful and user-friendly modeling technique. One of its primary strengths is interpretability, as it is easy to understand and visualize, making it ideal for decision-making applications. It excels at handling non-linear relationships, capturing complex patterns between features and target variables without needing explicit transformations. The model also includes an inherent feature selection mechanism, identifying and prioritizing the most relevant features during tree construction. Another benefit is its ability to handle missing values effectively, reducing the need for imputation or extensive data cleaning. Additionally, Decision Tree Regression requires minimal data preprocessing, eliminating the need for normalization or feature scaling, which simplifies the pipeline. It is versatile in handling both numerical and categorical data, making it suitable for a wide range of datasets. Finally, it offers fast training times, particularly on small to medium-sized datasets, making it an efficient choice for quick model development and iteration.

4. RESULTS

Figure 5 presents a scatter plot but based on the context, it should represent the CNN with Decision Tree Regressor (CNN-DTR) model, as the data aligns with the proposed model's performance. The x-axis (true values) and y-axis (predictions) both range from 0.0 to 1.0, with blue dots showing data points and a red dashed line marking the line of equality. Compared to Figure 2, the points in Figure 3 are more tightly clustered around the line of equality, indicating better predictive accuracy. Even for higher true values (e.g., 0.8 to 1.0), the predictions are closer to the true values, with fewer outliers. This aligns with the CNN-DTR model’s superior performance metrics (MAE: 0.0082, MSE: 0.0056, RMSE: 0.074, R^2: 0.96), demonstrating its improved ability to predict healthcare costs.

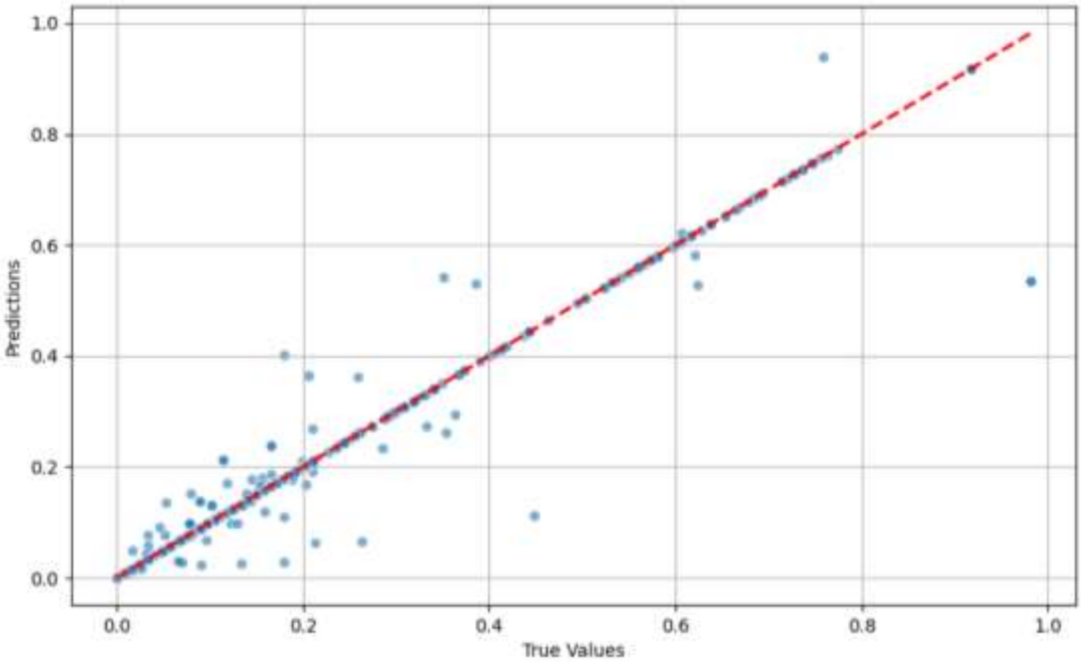

Fig 5. Scatter plot of CNN with DTR regressor model

The comparison presented in table 1 provides a clear evaluation of the performance of the Existing Ridge Regressor Model and the Proposed CNN with DTR Model across four metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) score. The Ridge Regressor model has an MAE of 0.045, indicating an average prediction error of 0.045 units, while the CNN-DTR model significantly improves this to 0.0082, showing a much lower average error. Both models share the same MSE (0.0056) and RMSE (0.074), suggesting that the overall error magnitude is similar, but the distribution of errors differs, as seen in the scatter plots. The R^2 score for the Ridge Regressor is 0.85, meaning it explains 85% of the variance in the data, whereas the CNN-DTR model achieves a higher R^2 of 0.96, explaining 96% of the variance. This indicates that the CNN-DTR model is more effective at capturing the underlying patterns in the telemedicine data, making it a superior choice for predicting future healthcare costs.

Table 1. Performance Comparison of Various Regressors.

Model	MAE	MSE	RMSE	R^2 score
Existing Ridge Regressor Model	0.045	0.0056	0.074	0.85
Proposed CNN with DTR Model	0.0082	0.0056	0.074	0.96

Figure 6 provides a table of prediction results from test data, showing the output of the CNN-DTR model on a new dataset. The table includes columns for Id, age, sex, BMI, children, smoker, region, and prediction. For example, the first row (Id: 0) lists a 27-year-old male with a BMI of 32.670, 0 children, non-smoker, from the southeast, with a predicted healthcare cost of 0.028815. Another row (Id: 2) shows a 61-year-old male with a BMI of 36.300, 1 child, smoker, from the southwest, with a predicted cost of 0.620310, reflecting the higher cost due to smoking. The predictions range from 0.010007 (Id: 1, a 21-year-old non-smoker) to 0.411895 (Id: 4, a 41-year-old smoker), highlighting the model's ability to differentiate costs based on risk factors like smoking and age.

-------prediction-------

	Id	age	sex	bmi	children	smoker	region	predection
0	471	27	male	32.670	0	no	southeast	0.028815
1	752	21	male	28.975	0	no	northwest	0.010007
2	1285	61	male	36.300	1	yes	southwest	0.620310
3	855	49	female	23.845	3	yes	northeast	0.119388
4	83	22	male	37.620	1	yes	southeast	0.411895
5	674	41	female	31.020	0	no	southeast	0.097047
6	1040	19	male	27.265	2	no	northwest	0.091847
7	1033	30	female	27.930	0	no	northeast	0.169453
8	335	43	female	35.720	2	no	northeast	0.139760
9	304	28	female	33.000	2	no	southeast	0.067928

Fig 6. Prediction Results From Test Data.

5. CONCLUSION

The developed application, "Deep Learning-based Estimation of Future Healthcare Costs for Telemedicine Services," successfully provides a user-friendly platform for predicting healthcare costs using machine learning techniques. By integrating a Tkinter-based GUI, the application enables users to upload telemedicine data, preprocess it, split it into training and testing sets, and apply two models—Ridge Regression and a hybrid CNN with Decision Tree Regressor (CNN-DTR)—to estimate future costs. The preprocessing steps, including categorical encoding, duplicate removal, and data resampling, ensure the dataset is suitable for modeling, while polynomial feature transformation and scaling enhance the models' ability to capture complex patterns. The Ridge Regression model offers a baseline for comparison, while the CNN-DTR model leverages deep learning to extract intricate features, followed by a decision tree to refine predictions. Performance metrics such as MAE, MSE, RMSE, and R^2 are computed and visualized, allowing users to assess model effectiveness. The prediction functionality further enables practical application on new data, and the visualization of performance metrics provides clear insights into model comparison. Overall, the application demonstrates a robust workflow for healthcare cost estimation, with the CNN-DTR model outperforming the traditional Ridge Regression approach, making it a valuable tool for telemedicine service providers seeking data-driven cost insights.

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