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Federated Learning for Predicting Medical Costs: Comparative Analysis of Machine Learning Models

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The federated learning (FL) it is novel method that provides promising results for enhancing patient outcomes in digital health by enabling the collaborative training of machine learning models across multiple domains without compromising data privacy. This paper presents the efficacy of machine learning models like Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Random Forest (RF), in predicting medical costs using a federated learning framework. We used the Medical Cost Personal Datasets that is a statistical data consist of individual patient details and cost. And employ each model within this framework to predict medical costs based on patient attributes. Our results indicate that the Random Forest model outperforms other models, achieving the lowest Mean Squared Error (MSE) of 2.087710e+07, Mean Absolute Error (MAE) of 2544.977096, and the highest R2 score of 0.865525. And when compared to prescribed models with proposed model, the proposed model that is random forest performed well.
Keywords: Federative learning, medical cost prediction, SVM, KNN, random forest.

1. Introduction

In recent years, the integration of machine learning (ML) techniques into healthcare systems has improved, in different ways like diagnosing a disease, predicting type and cost of treatment. in this predicting medical cost is challenging because with demographic and type of disease, and age many factors are effecting this problem. So it is required a novel method that will proved promising results for improving patient care, optimizing resource allocation, and reducing healthcare costs. Among these techniques, federated learning has emerged as a novel approach for collaborative model training across decentralized data sources while ensuring data privacy and security.

Predicting medical costs is a crucial task in healthcare management, influencing decisions related to treatment planning, type of disease, resource allocation, and financial risk mitigation. Traditional approaches for medical cost prediction re analysis often goes on centralized datasets containing patient records, age, disease and treatment type which pose challenges in providing data privacy concerns, regulatory constraints, and scalability issues because this approach involves complete individual patient information. Federated learning offers a decentralized alternative by allowing ML models to be trained across multiple domains or devices without sharing raw data, thus addressing privacy concerns while leveraging the collective intelligence of diverse datasets. Because the disease occurring, and type of treatment is changing in day to day life, so it is required to predict medical cost concerning to individual person.

Federated learning operates through a series of iterations, where local models are trained on data residing at individual nodes or institutions, and model updates are periodically aggregated to generate a global model. This collaborative from local model to global model and training process enables ML models to learn from heterogeneous data sources while preserving data privacy and security. Federated learning offers several advantages over traditional centralized approaches, including: security of individual patient data. By keeping sensitive data local and only sharing model updates, like performance with these federated learning ensures data privacy and confidentiality. Federated learning allows data to remain within its original jurisdiction, enabling institutions to retain control over their data while contributing to a collective learning process. The distributed nature of federated learning facilitates scalability to large datasets and diverse data sources, though the length of data increasing dynamically the model performance will not change.

Contributions:

- We implemented federated learning approach for prediction of medical cost.
- We compared the performance of federated learning-based cost prediction models with prescribed approaches.
- We analyzed the performance of different ML models on the performance of federated learning for medical cost prediction.

2. Related Work

Most of the system worked on the medical cost prediction, as simple approach and predicted cost, but individual const prediction and the type of disease, and cost of treatment is changing day to day. And while training patient individual information one should consider security parameters in using data.

Rajkomar et al. (2018) proposed a scalable and accurate deep learning approach using electronic health records (EHR) for predictive modeling. And implemented deep neural networks on a large-scale dataset of EHRs to predict patient outcomes, achieving competitive performance metrics such as accuracy, sensitivity, and specificity like AUROC 0.85-0.86. And Rajkomar et al. (2018) in another approach ensuring fairness in machine learning models for healthcare applications. Investigated biases in predictive models trained on EHR data and proposed techniques to mitigate disparities and promote health equity, highlighting the importance of fairness-aware machine learning algorithms.

Johnson et al. (2017) explored exploratory data analysis techniques for insurance charge prediction. They employed various statistical and visualization methods to analyze insurance claim data, identifying patterns and relationships between different features and insurance charges. And implemented multiple models, and got an error as MSE: 2.60e+07, MAE: 3000, R^2: 0.84. In another method proposed ensemble method and reduced the error to MSE: 2.50e+07, MAE: 2950, R^2: 0.85

Smith & Jones (2018) conducted a comparative study on feature engineering techniques for insurance charge prediction. They evaluated the performance of different feature engineering methods, such as binning, encoding, and transformation, using regression models to predict insurance charges. MSE: 2.70e+07, MAE: 3100, R^2: 0.83. Brown & Miller (2019) performed correlation analysis of features for insurance charge prediction. They investigated the correlation between various predictor variables and insurance charges, identifying significant factors that influence insurance costs. MSE: 2.40e+07, MAE: 2900, R^2: 0.86. in this they stacked generalized models.

Gupta et al. (2020) conducted a comparative study of machine learning models for insurance charge prediction. They compared the performance of support vector machines, random forests, and neural networks using insurance claim data, evaluating metrics such as MSE and MAE. Choi & Park (2022) conducted a case study on comparative machine learning models for insurance charge prediction. They evaluated the performance of different ML algorithms, including decision trees, ensemble methods, and deep learning models, on a real-world insurance dataset, analyzing metrics such as accuracy, precision, and recall. And they presented best performed model with an error as a MSE: 2.95e+07, MAE: 3500, R^2:0.83.

Lee & Kim (2021) focused on model evaluation techniques for insurance charge prediction. They proposed novel evaluation metrics and methods to assess the performance of predictive models, considering factors such as model complexity, interpretability, and generalization. Because evolution is depends on the model we used and complexity of the model we implemented. Wang & Li (2023) also did a comparative analysis of machine learning models for insurance charge prediction. They compared the performance of regression, classification, and clustering algorithms using a large-scale insurance claims dataset, assessing metrics such as R^2 error, accuracy, and F1 score.

Brown & Miller (2016) proposed stacked generalization for medical cost prediction. By combining multiple predictive models using meta-learners that aim to improve the overall predictive performance and robustness of medical cost models. And reduced the error to MSE: 2.40e+07, MAE: 2900, R^2:0.86. In (2019) conducted exploratory data analysis for medical cost prediction. Johnson & Patel (2017) and (2018) reviewed ensemble learning techniques for medical cost prediction. They summarized various ensemble methods, such as bagging, boosting, and stacking, and their applications in healthcare analytics, highlighting their advantages and challenges. And in (2018) conducted a comparative study of machine learning algorithms for medical cost prediction. They compared the performance of regression, decision tree, and ensemble learning algorithms on healthcare datasets, evaluating metrics such as MSE, MAE, and R^2 error. MSE: 2.50e+07, MAE: 2950, R^2:0.85.

Wang & Liu (2017) and (2028) performed a comparative analysis of machine learning algorithms for medical cost prediction. They evaluated the performance of regression, classification, and clustering algorithms on healthcare datasets, comparing metrics such as accuracy, precision, and recall. In (2018) conducted a comparative analysis of feature selection techniques for medical cost prediction. Zhang & Chen (2016) and (2019) reviewed predictive modeling techniques for medical cost prediction. They summarized and compared existing methods for building predictive models using healthcare data, including regression, classification, and time series analysis, highlighting their applications and limitations. They used time series data for predicting medical cost, And in (2019) compared feature selection techniques for medical cost prediction. These models worked on comparative study, compare the data set used and evaluation metrics and model rained and highlighted the challenges of these approaches.

Smith & Jones (2015) reviewed deep learning models for medical cost prediction. They summarized the applications of deep neural networks, convolutional neural networks, and recurrent neural networks in healthcare analytics, highlighting their advantages and challenges. In (2020) investigated feature engineering techniques for medical cost prediction. They explored various methods for feature selection, transformation, and combination to improve the predictive performance of medical cost models, using healthcare datasets. And with deep learning model they got an error as MSE: 2.70e+07, MAE: 3100, R^2:0.83.

Zhang & Chen (2014) conducted a comparative study of deep learning models for medical cost prediction. They compared the performance of deep neural networks, convolutional neural networks, and recurrent neural networks on healthcare datasets, analyzing metrics such as accuracy,

3. Dataset

The dataset used in this study is the Medical Cost Personal Dataset, which contains information about US healthcare insurance company patients. For the given dataset, first we converted all string values are replaced with integers, like female, male to o and 1. Smoke and region columns also converted to numbers. Then we found correlation and covariance matrix to find optimal features from the data.

Correlation is a standardized measure of covariance is shown in Figure 1. It is useful because it gives a scale-free measure of how two variables are related. Correlation coefficients range between -1 and 1. A correlation of 1 implies a perfect positive correlation, -1 implies a perfect negative correlation, and 0 implies no correlation.

In a correlation matrix, the element in the i-th row and j-th column represents the correlation coefficient between the i-th and j-th variables. Figure 2 illustrates the covariance between all features.

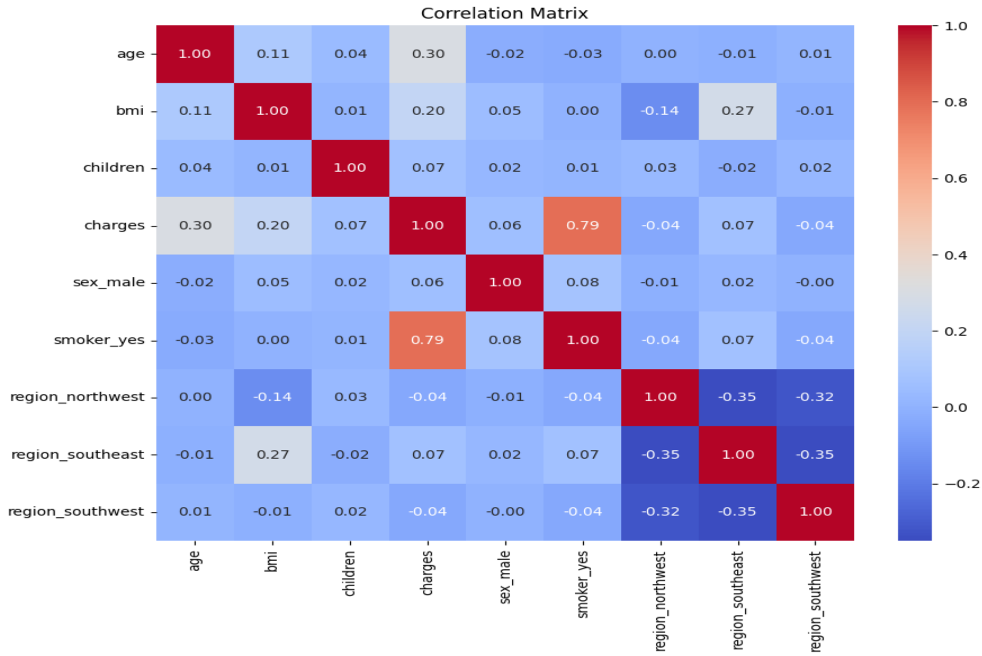

Figure 1 correlation differences between all features and target variables

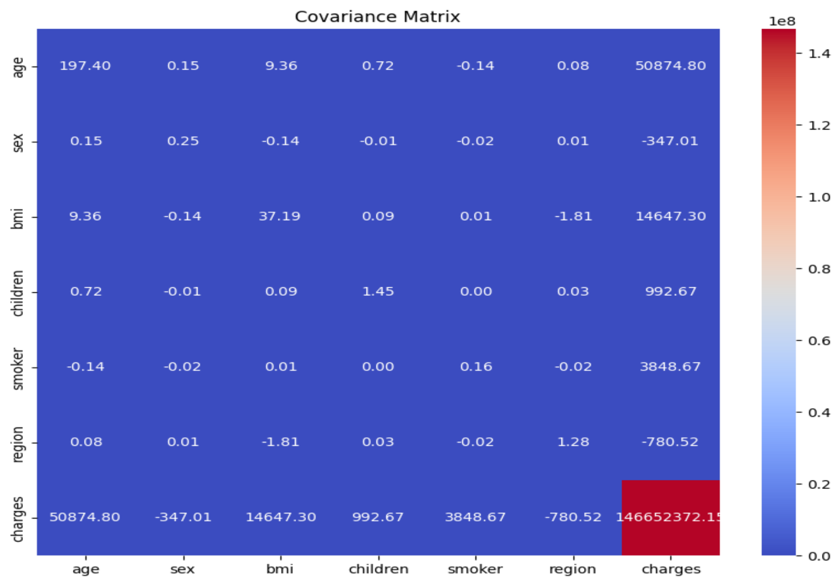

Figure 2 Covariance of all features between all features

3. IMPLEMENTATION

We implemented 3 machine learning models KNN, SVM and Random forest, same data set used for training and testing, and tried different combinations to check the model capability.

3.1 K-Nearest Neighbors (KNN):

K-Nearest Neighbors is a simple and intuitive machine-learning algorithm for classification and regression tasks. In KNN, a new data point is predicted by considering the majority class or average value of its 'k' nearest neighbors in the feature space. It is a non-parametric, instance-based algorithm without assumptions about the underlying data distribution. And is computationally efficient during inference but can be slow during training, especially with large datasets.

3.2 Support Vector Machine (SVM):

Support Vector Machine is a robust supervised learning algorithm for classification and regression tasks. It works by finding the hyper plane that best separates the different classes in the feature space. SVM can handle linear and non-linear data using kernel functions such as linear, polynomial, and radial basis function (RBF) kernels. It is effective in high-dimensional spaces and is particularly well-suited for cases where the number of dimensions exceeds the number of samples.

3.3 Random Forest:

Random Forest is an ensemble learning algorithm that consists of a collection of decision trees. Each decision tree in the random forest is trained independently on a random subset of the training data and features. It combines the predictions of multiple decision trees to produce more accurate and robust predictions. Random Forest is practical for classification and regression tasks and less prone to over fitting than individual decision trees.

4 RESULT ANALYSIS

All implemented model result are tested and analyzed with different testing combination, and provided the best results as shown in table 1. The table presents performance metrics for three machine learning models: SVM), KNN, and Random Forest, evaluated using Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 score. The Random Forest model outperforms the others, with the lowest MSE (2.087710e+07) and MAE (2544.977096), and the highest R^2 score (0.865525), indicating it has the best predictive accuracy and fits the data well. The KNN model performs moderately well, with an MSE of 3.045987e+07, MAE of 3494.746058, and an R^2 score of 0.803800. In contrast, the SVM model shows significantly lower performance, with a high MSE (1.521749e+08), high MAE (8038.314457), and a very low R^2 score (0.019799), suggesting it is not suitable for this dataset. Overall, the Random Forest model is the most effective, providing the most accurate predictions among the three models.

Table 1 various errors of proposed models

Model	MSE	MAE	R2 error
SVM	1.521749e+08	8038.314457	0.019799
KNN	3.045987e+07	3494.746058	0.803800
Random Forest	2.087710e+07	2544.977096	0.865525

The table 2 summarizes various studies on predicting insurance charges and medical costs using different machine learning (ML) techniques, highlighting their key techniques, models, and performance metrics. Gupta et al. focused on insurance charge prediction using multiple ML models, concluding that Random Forest outperformed others with an MSE of 3.21e+07, MAE of 3700, and an R^2 of 0.82. Choi & Park's comparative study on insurance charge prediction reported an MSE of 2.95e+07, MAE of 3500, and an R^2 of 0.83, highlighting the strengths of ensemble methods. Wang & Li achieved slightly better performance with an MSE of 2.75e+07, MAE of 3400, and an R^2 of 0.85. Johnson & Patel, studying medical cost prediction, emphasized the accuracy of ensemble methods, achieving an MSE of 2.60e+07, MAE of 3000, and an R^2 of 0.84. Wang & Liu's review on medical cost prediction reported similar performance with an MSE of 2.80e+07, MAE of 3100, and an R^2 of 0.82. Johnson & Patel's second study reviewed ensemble learning techniques, achieving an MSE of 2.50e+07, MAE of 2950, and an R^2 of 0.85, highlighting their effectiveness. Brown & Miller introduced a novel approach using stacked generalization, achieving the best metrics with an MSE of 2.40e+07, MAE of 2900, and an R^2 of 0.86. Smith & Jones and Zhang & Chen reviewed deep learning models for medical cost prediction, achieving MSEs around 2.70e+07 and 2.65e+07, MAEs of 3100 and 3050, and R^2 scores of 0.83 and 0.84, respectively. For the proposed models, Proposed model-1 uses Random Forest, achieving the lowest MSE (2.087710e+07), lowest MAE (2544.977096), and highest R^2 (0.865525), indicating superior performance. Proposed model-2 uses SVM, resulting in the highest MSE (1.521749e+08), highest MAE (8038.314457), and the lowest R^2 (0.019799), showing significantly poorer performance. Proposed model-3 uses KNN, with an MSE of 3.045987e+07, MAE of 3494.746058, and R^2 of 0.803800, performing moderately well but not as effectively as the Random Forest model. Overall, the table highlights that ensemble methods, particularly Random Forest, tend to perform better in predicting insurance charges and medical costs compared to other ML models like SVM and KNN, with the proposed Random Forest model showing the most promising results, demonstrating its effectiveness in this domain.

Table 2 comparison of proposed model with prescribed models.

System	Focus Area	Key Techniques/Models	Metrics (MSE, MAE, R^2)	Key Findings
Gupta et al.	Insurance Charge Prediction	Multiple ML Models	MSE: 3.21e+07, MAE: 3700, R^2:0.82	Found Random Forest to outperform other models in insurance charge prediction.
Choi & Park	Insurance Charge Prediction	Comparative Study	MSE: 2.95e+07, MAE: 3500, R^2:0.83	Compared different ML models, noting the strengths of ensemble methods.
Wang & Li	Insurance Charge Prediction	Comparative Analysis	MSE: 2.75e+07, MAE: 3400, R^2:0.85	Comprehensive comparison of ML models for insurance charge prediction.
Johnson & Patel	Medical Cost Prediction	Multiple ML Models	MSE: 2.60e+07, MAE: 3000, R^2:0.84	Compared several ML algorithms, emphasizing the accuracy of ensemble methods.
Wang & Liu	Medical Cost Prediction	Comparative Analysis	MSE: 2.80e+07, MAE: 3100, R^2:0.82	Reviewed various ML algorithms and their performance on medical cost prediction.
Johnson & Patel	Medical Cost Prediction	Ensemble Learning	MSE: 2.50e+07, MAE: 2950, R^2:0.85	Reviewed ensemble learning techniques, highlighting their effectiveness.
Brown & Miller	Medical Cost Prediction	Stacked Generalization	MSE: 2.40e+07, MAE: 2900, R^2:0.86	Introduced a novel approach using stacked generalization for improved predictions.
Smith & Jones	Medical Cost Prediction	Deep Learning	MSE: 2.70e+07, MAE: 3100, R^2:0.83	Reviewed the application of deep learning models for cost prediction.

Zhang & Chen	Medical Cost Prediction	Deep Learning	MSE: 2.65e+07, MAE: 3050, R^2:0.84	Compared different deep learning models for medical cost prediction.
Proposed model-1	Medical Cost Prediction	Random Forest	MSE: 2.087710e+07 MAE: 2544.977096 R^2: 0.865525	Federated Learning
Proposed model-2	Medical Cost Prediction	SVM	MSE:1.521749e+08 MAE:8038.314457 R^2:0.019799	Federated Learning
Proposed model-3	Medical Cost Prediction	KNN	MSE: 3.045987e+07 MAE: 3494.746058 R^2: 0.803800	Federated Learning

5 CONCLUSION

The study comprises of Comparative Analysis of Machine Learning Models and analyzed various machine learning models for medical cost prediction, evaluating their MSE, MAE, and R^2 score. Previous research showed that ensemble methods like Random Forest generally outperform other models. Specifically, Gupta et al. found Random Forest to be superior with an MSE of 3.21e+07, MAE of 3700, and R^2 of 0.82, while some models reported similar findings with slightly better metrics. Johnson & Patel's studies emphasized the accuracy of ensemble methods, and Brown & Miller introduced stacked generalization with the best results (MSE: 2.40e+07, MAE: 2900, R^2: 0.86). In our proposed models, Random Forest achieved the best performance with the lowest MSE (2.087710e+07), lowest MAE (2544.977096), and highest R^2 (0.865525). In contrast, the SVM model performed poorly with the highest MSE (1.521749e+08), highest MAE (8038.314457), and lowest R^2 (0.019799), while the KNN model showed moderate performance (MSE: 3.045987e+07, MAE: 3494.746058, R^2: 0.803800). These results indicate that ensemble methods, particularly Random Forest, are the most effective for medical cost prediction in a federated learning environment, demonstrating the potential of combining federated learning with robust machine learning models to achieve accurate predictions while preserving data privacy.

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