Global Health Expenditure Analysis and Predictions

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Abstract - *This study analyzes the trends of global health expenditures including patterns of the real gross domestic product (GDP) and health expenditures as a percentage of GDP for almost 200 countries in 2000 and 2022 . Principal component analysis was adopted to reduce dimensionality, thereby discerning the major expenditure-influencing factors and simplifying the complexity of the dataset. It aided in understanding variable importance, which was useful in further predictive modeling. Four ways for forecasting health expenditures were employed: AR (Autoregressive), MA (Moving Average), ARMA, LSTM (Long Short-Term Memory) networks. The AR and MA gave strong statistical assertions about past and recent trends, while ARMA was a hybrid method that combined autoregressive and moving average components to fit more complex time-dependent structures within the data. while the LSTM model learned the long-term dependency and non-linear relationships existing in the data. Two distinct LSTM models, Uni-variable (UV) and Multi-variable (MV), were developed based on various indicators of healthcare expenditure. A comparison of these methods indicated the strength of each of the methods in context with performance, shedding light on how both traditional statistical methods and deep learning techniques may be successful in predictive analytics.*

Keywords—Principal Component Analysis, Dimensionality reduction, Healthcare Spending Patterns, Long Short-Term Memory, Autoregressive Model, Moving Average Model.

1. INTRODUCTION

Health care spending acts as a key determinant for the capacity of the health system, the resilience of the economy, and the general state of public welfare in a nation. Funding streams in a health care system are fundamentally essential in shaping access to medical services, infrastructural development, and advancement in medical research. One of the most important financial indicators is Current CHE_GDP: Health Expenditure as a percentage of GDP; indicates the level of relative investment a country is making in health care. This study will focus on analysing and forecasting CHE-GDP trends in about 200 countries starting from 2000 to 2022 to fathom a clear picture of the global health care financing framework.

Over the last two decades, the landscape of global health has witnessed multiple transformations expenditure due to economic dynamics, population aging, technological advancements, inflation in healthcare, and public health crises like COVID-19. These changes have warranted the need for further analytical techniques to uncover expenditure trends, advocate financial sustainability, and assess future scenarios. For government officials, researchers, and health institutions, such knowledge provides a basis to enhance resource allocations, improve financial planning, and sustain health systems in the future. Data is collected from the World Health Organization (WHO) Global Health Expenditure Database, providing data for nearly 200 countries between 2000 and 2022.This dataset covers all aspects related to government and private contributions toward health, per capita expenditure, and other economic trends concerning the global healthcare systems. The size and intricacy of the dataset offer a variety of variables and correlations that are outside the purview of traditional analysis in order to comprehend the process of deriving meaning from the data. Since the data are high-dimensional by nature, identifying the key variables influencing healthcare spending presents both a problem and an opportunity for sophisticated methodologies.

Due to the high dimensionality and complexity of the data presented in this study, they have been analysed using Principal Component Analysis (PCA) to reduce duplication without sacrificing the most significant factors affecting changes in CHE_GDP. PCA decreases the difficulty of data interpretation by naming key contributors to healthcare spending change trends while sustaining the fundamental structure of the data.

To perform the forecasting of future CHE_GDP values, four different predictive modeling techniques were applied Autoregressive (AR) Models Using past values of CHE_GDP to predict future trends based on time-dependent relationships. Moving Average (MA) Models are utilizing methods that capture short-lived deviations concerning healthcare expenditure from smooth past variations. Autoregressive and Moving Average (ARMA) Model with both autoregressive and moving average components, modeling current CHE_GDP based on past dependencies and short-run changes. Since then Long Short-Term Memory Networks (LSTMs) with Deep learning-based were introduced to capture long-term dependencies and nonlinear patterns in time-series data. While the classical AR, MA and ARMA models may have helped one derive certain statistical. conclusions about past spending behavior, they poorly capture complex long-term relationships; this limitation is addressed in the scope of this study through the implementation of univariate and multivariate LSTMs. Univariate LSTM will extrapolate future CHE_GDP from previous records. Multivariate LSTM will exploit other additional economic- and healthcare-related variables such as government- and private-sector healthcare contributions to predict more accurately.

2. LITERATURE SURVEY

[3]To examine health expenditure worldwide, the existing system mostly uses a statistical and descriptive approach and does not deal well with the relations and dynamics of health expenditure issues. With their crude measuring unit, traditional methods can hardly reveal patterns or make comparisons between countries nuanced. The existing system estimating global health expenditure is based on inter-country domestic health expenditure evaluations for 195 countries and territories and encompasses three main funding sources, that is, expenditure incurred by government, privately financed out-of-pocket spending and pre-paid private health spending. data from 195 countries from 1995 to 2016, as well as DAH data from 1990 to 2018, to estimate trends in global health spending. It also includes development assistance for health (DAH) over 1990–2018. This approach, through modelling uncertainty, creates the dataset necessary to estimate total health expenditure categories and DAH despite a variety of issues presenting challenges in assembling complete or really good quality thus supporting the health financing transition theory. Future scenarios for health spending have been forecasted using linear mixed-effects models, all having time series specifications These predictors have been drawn from national health accounts, budget reports, and revenue tracking systems after standardization and conversion from inflation-adjusted 2018 US dollars.

[8]The study by Muremyi et al. (2018) examines a massive exercise in predicting out-of-pocket health expenditure in Rwanda using a variety of machine learning algorithms. The authors introduced a range of models, including multivariate adaptive regression splines (MARS), decision trees, random forests, gradient boosting, and treenet. The model with the highest accuracy of 87% was produced out of the above denoting a treenet model. One of the major predictors for all models investigated is the total consumption of households in terms of household consumption. Therefore, its relevance in predicting health costs is significant, as this information will be crucial for policy formulation on healthcare financing, particularly in terms of increasing domestic public budgets to attain Universal Health Coverage (UHC). However, there are certain downsides to the study. It takes a single dataset of 14,580 households (EICV5) and hence does not represent the general population or address its geographical differences across the country. Moreover, although the models predicted well, it does not take account of possible issues of interpretability in the models, as this would limit knowing how and why some of the most relevant predictors, i.e. household consumption, are so powerful.

[9]This existing research deepens one's understanding of the complex (1) the effect of public health expenditure on health status; (2) the role of health status in influencing economic development. Health advancements increase labor productivity and, consequently, economic growth, according to Bloom and Canning (2000) and Weil, (2007). In the Nigeria context, however, Anyanwu and Erhijakpor (2009) find that increased health expenditure translates directly into better health outcomes whereas Aregbesola and Khan (2018) contend that poor funding makes health less impactful to the wider economy. Seer's, (1972), Three Pillars model; the poverty, inequality, and unemployment are then blended as an Economic Development Index alongside the techniques of Principal Component Analysis - PCA, through Filmer and Pritchett, (2001). Those models have been widely used in methodology in simultaneous equation models. Baldacci et al. (2008) and Barro (1996) show a health expenditure indirect impact on economic growth via health status using such models, whereas Acemoglu and Johnson (2007) argued on the direct effect on GDP. Advanced econometrics such as Three-Stage Least Squares (3SLS) by Zellner and Theil (1962) improved efficiencies in estimation by eliminating endogeneity and simultaneity problems. This study, therefore includes a new Economic Development Index (EDI) as well as Health Status Index developed using PCA with simultaneous equation modeling by way of 3SLS estimation for a holistic view of Nigeria's health-economy dynamic.

[11]This study covers global health financing trends for 184 countries between 1995 and 2014. Health expenditures are estimated using programmatic the latest reports national estimates and 964 National Health Accounts. They were converted into currency adjusted using inflation-adjusted purchasing power. Economic growth and health financing are interrelated., and time is estimated using non-linear regression models. Results show that increase in economic development increases health expenditure," reducing reliance on out-of-pocket (OOP) payments and aid while increasing government spending". The most significant increases in spending have occurred in countries with the highest income. The contrasts for the lowest-income countries are that they continue to rely on OOP and aid. Although modest, aid growth has not eradicated the inequities in funding, thus pointing towards the need for effective strategic healthcare financing policies In low-

income countries, out-of-pocket health spending accounted for 29.1% of the total health spending in 2014, compared to 58.0% in lower-middle-income countries. There exist variations in spending across different countries, the variations pointing to the fact that some countries exceed their expectations while others fall short of their goals. These things indicate that economic growth does not guarantee the existence of adequate pre-paid health resources and must necessarily have strategic policy approaches for continued and fair healthcare financing.

[13]Prediction of health care costs is a field that has increasingly gained attention because costs associated with health care are rising so fast that they become a budget for government expenditure and an individual's pocket. Traditional statistical methods in time series forecasting have extensively been used; however, over time, more and more machine learning techniques are being adopted by researchers because of their powerful ability to learn complex relationships. Different researches have effectively applied their various models, including Support vector regression (SVR), decision tree regression (DT), and Gaussian process regression (GPR). SVR is known for strong generalization power even with small datasets, while DT is a very interpretable means of prediction but is prone to overfitting. On the contrary, GPR as a probabilistic model is able to quantify uncertainty, yet its computational burden is quite high. Determinants of health care expenditure include economic indicators such as GDP per capita, unemployment rate; demographic factors like age and urbanization; and healthcare system parameters such as physician density and hospital bed availability. Among machine learning models, studies have also indicated that SVR usually outperforms others in prediction accuracy; thus, it is an appropriate model for predicting health expenditure.

3. METHODOLOGY

3.1 Introduction

The procedure for forecasting global health expenditures passes through various stages, starting from the data collection and preprocessing activities of the WHO Global Health Expenditure Database. The dataset with 4405 rows and 4120 columns cleaned was done by imputing the median value for missing data, followed by MinMaxScaler standardization and further dimensionality reduction with PCA(224 components explaining 95% variance).

The Augmented Dickey-Fuller (ADF) test was performed on CHE (% GDP) time series data to ascertain reliable time-series forecasting. The results indicated a test statistic of -12.57 with a p-value of 1.97e-23, well below the 0.05 threshold, confirming stationarity of the series. The time series was analyzed by means of the rolling statistics analysis to observe the moving average and the standard deviation within the set timeframe. The rolling mean and rolling standard deviation results were interpreted to visualize trends and fluctuations over time. The rolling means show a gradual rise in healthcare expenditures, while the rolling standard deviation has depicted stability except for significant fluctuations around the year 2020, possibly due to the COVID-19 pandemic.

Training data upto the time of prediction is critical in tabulating Autoregressive (AR), Moving Average(MA), ARMA model,to ensure past dependencies are captured effectively in the prediction. Classical Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) plots and Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Alongside, deep learning approaches operated Univariate LSTM (predicting CHE_GDP using the past values) and Multivariate LSTM(leveraging additional economic indicators like GDP, GGHE-D, PVTD, and EXT). Both LSTMs were designed with multiple LSTM layers, Dropout, BatchNormalization, and Optimizer Adam, trained with an 80% train, 20% test split over 100 epochs.
Evaluation metrics include MAE, MSE, RMSE, and MAPE to benchmark AR, MA, ARMA, and LSTM models, while ReduceLROnPlateau was sued to enhance convergence of the model. The five years ahead forecast represents trends in CHE_GDP of different countries. Once the models have been trained and evaluated, forecasts are prepared for the next 5 years for each country. These forecasts are then compared with actual recorded data to determine the level of precision and reliability of the forecast produced by the model. Finally, a detailed evaluation of the models is conducted in terms of their ability to generate the trend of health expenditure projections over time.

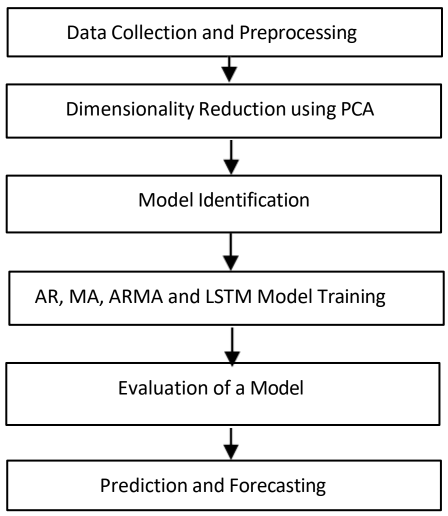

Fig -1: Methodology

3.2 Data Collection and Preprocessing

The dataset for this project contains data on health expenditure on global health for many different countries and over many years. It includes such variables as country code, region, income group, health expenditure (che), gghed ,pvtd etc. The data is between the years 2000 and 2022 and is downloaded from WHO databases, which makes it well-esteemed and complete. The first phase: Preprocessing-preparation, which cleans, formats the data, and removes missing data and inconsistencies in the dataset. This includes handling missing entries and duplicate entries and converting categorical features (e.g., country, region) into numericals, which can be subsequently analysed. Feature Scaling Standardizes the dataset so that all features contribute equally to the overall performance of the model.

3.3 Feature Engineering and Dimensionality Reduction

Because of the many features that are involved in the dataset, PCA is applied for dimensionality reduction and extraction of the most relevant components. Essentially, for PCA, trivial features that will help to explain variance in the data are identified and, hence, facilitate the handling of the smaller dataset that maintains all vital information. After the PCA transformation, we retained 224 components that are quite representative of the underlying patterns of the global health expenditure data. PCA-generated components are used to study the relations and trends within the health expenditure data.

3.4 Forecasting with AR,MA,ARMA and LSTM.

For the forecast of future health expenditures for individual countries, we integrated a series of time series models, including Autoregressive (AR), Moving Average (MA), and Long Short-Term Memory (LSTM).

*a)*AR Model: AR Model: The prediction of future health spending (CHE_GDP) is done using an Auto Regressive (AR) model which is based on its past values thereby assuming linearity to all the previous observations. In identifying the order of lag (p) for which Using each nation's CHE_GDP data, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were explored. To identify this, Autocorrelation Function (ACF) and Partial Auto correlation Function (PACF) was then used relevant past values-the meaningful last lag, according to PACF, was optimal p.

For each country, the dataset was first sorted by year and groups were formed accordingly. The optimal lag order for the AR models was determined by fitting the model for lags of 1 through 5 and identifying the lag with the lowest AIC and BIC score. The data was then split into training and test sets in 80-20 proportions. The Auto Reg model was then developed using the CHE_GDP data history, whereas prediction was executed to the test set. Model performance was then measured using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). For future health expenditure forecasting, CHE_GDP was predicted for five years (2023-2027), with results stored in an Excel file. Finally, line plots were prepared to compare the actual values with predicted values, and future forecasts are presented with enhanced styling for clarity.

$$yt=c+\sum \phi i yt-i+\epsilon t \text{ (i.e: i=1 to p)}$$

yt stands for the CHE_GDP at time t, c is a constant, ϕi are AR coefficients, , p is the optimal lag, ϵ_t is the error term.

b) MA Model: The Moving Average (MA) model captures random noise and smoothens out short-term fluctuations and is used along with the AR model. The MA model works by deriving a relationship between the value of the series and past error terms. Thus, it gives as follows about the MA model-the present value is a linear combination of past errors:

$$yt=\mu+\sum \theta i \epsilon t-i+\epsilon t \text{ (i.e: i=1 to q)}$$

Here, μ is the mean of the series, θ_i are the moving average coefficients, q is the order of the model, and ϵ_t is the error term. The implemented MA model to forecast CHE-GDP was the year-wise sorting of the dataset and grouping by each country. Thus, the optimal lag (q) for each country was ascertained by fitting MA models of different orders (from 1 to 5) into the data and selecting the one that minimizes MAE. Data set was divided into training (80%) and testing (20%), and the model was trained using the past historical values of CHE_GDP. Predictions were evaluated using MAE, RMSE, and MAPE, and the model with optimal performance was used to forecast health expenditure for the next five years (i.e. 2023-2027).

c) LSTM Model: The health expenditure data has been sequenced to train The model employs three LSTM layers with respective sizes of 128, 64, and 32 units. All the three are architected to seize on the complexities inherent in temporal interrelations prevalent within the given data. Additionally, a 30% dropout rate is introduced in each layer to prevent overfitting while the inclusion of batch normalization is intended to enhance stability. The last output layer is a dense layer, with a single neuron that predicts the future values of CHE_GDP. The model was then compiled using the Adam optimizer, applying Mean Square Error (MSE) as the loss function and Mean Absolute Error (MAE) as a secondary performance measure. The LSTM model sequences are derived from a 5-year window of the past. The dataset is split into two categories: 80% for training and 20% for testing for a balanced evaluation.

The batch size of 64 ensures the training of the LSTM model across 100 epochs, to enhance learning further. A ReduceLROnPlateau callback is introduced to automatically change the learning rate when there is no improvement in validation loss, making the convergence process better. The trained model is then suited to rolling forecasting where the next 5f years of health expenditures are predicted for each country involved. Hence, it assists policymakers' foresight of possible funding gaps, enabling them to allocate resources optimally.

MAE, MSE, RMSE, and MAPE are the evaluation indices which are used to measure the performance of the model. They are used as indicators of the level of precision and reliability of the model across the nations.

4. RESULTS AND DISCUSSION

The time series data of CHE as % of GDP (chegdp) were subjected to the Augmented Dickey-Fuller (ADF) test employed to check stationarity. Test yielded a statistic of -12.57423 with p-value 1.97e-23, which is much lower than the 0.05 limit. The critical values for the tests at 1%, 5%, and 10% confidence levels stand at -3.4318, -2.8622, and -2.5671, respectively. Since the test statistic value is less than all of the critical values, hence we reject the null hypothesis of unit root. Therefore, the series is stationary.

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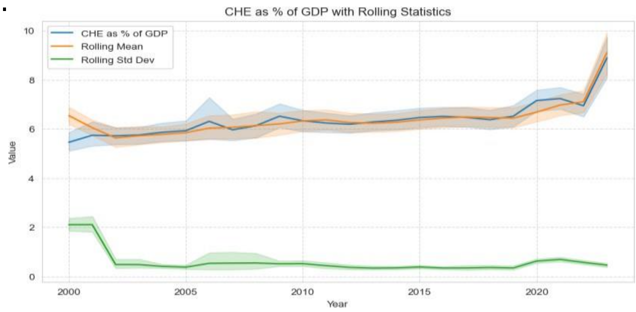

Fig -2: CHE_GDP Rolling Statistics

To visualize the moving average and its rolling standard deviation over time, rolling statistics analysis was obtained. Very gradually over a long period, the rolling mean is in a steady upward trend, suggesting Health expenditure as a percentage of the GDP is increasing. Throughout the observation period, the rolling standard deviation captures a rather low level of variance, suggesting fluctuations in expenditure are pretty well-controlled, with the exception of a strong spike in 2020, possibly because of the COVID-19 pandemic. The increase in CHE as a percentage of GDP being observed over time reflects the increasing level of financial burden on healthcare systems around the world. The steady state in variance as indicated by the rolling standard deviation shows that even though expenditures are on the increase, their behaviour remains predictable with a few exceptions due to exogenous shocks such as the COVID-19 pandemic, thus calling for viable healthcare funding policies to sustain equitable financial provision in the days ahead.

Forecast with AR Model: PACF and ACF plots were used, as well as AIC and BIC values to determine the AR model order so that the trade-off between complexity and goodness-of-fit was taken into account.

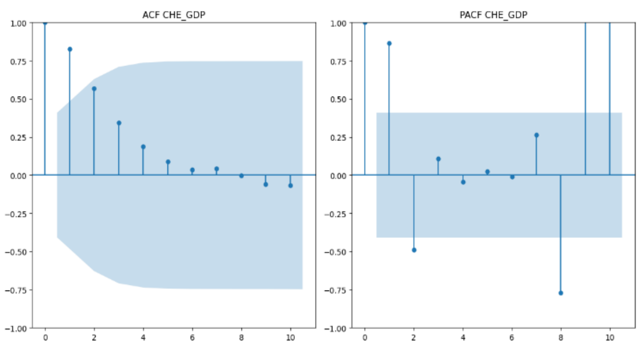

Fig -3: ACF and PACF Plot for India.

Optimal Lag Selections: AIC suggested lag is 2, BIC suggested lag is 2. The model finally selected was AR(2).

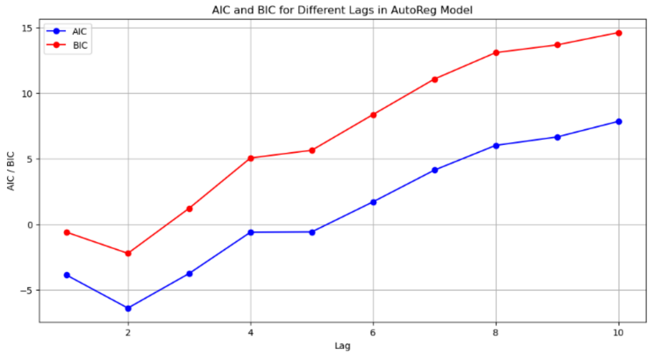

Fig -4:.AIC and BIC for Different Lags in AR model

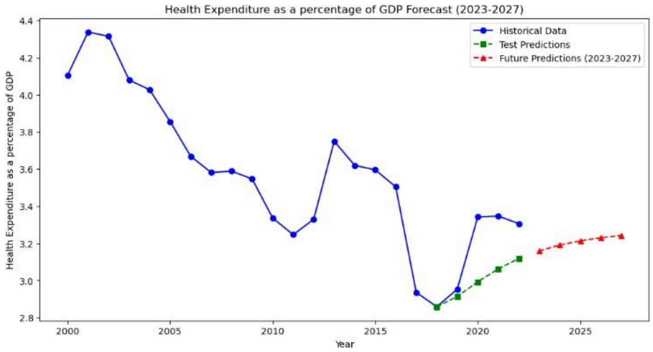

Fig -5: CHE_GDP predictions of India

In India, CHE_GDP has historically been characterized by fluctuations involving a decline since the early 2000s, a more marked fall around 2015, and a slow recovery thereafter starting from 2020. The AR(2) model predicts CHE_GDP to slowly rise from 2023-2027, showing an increasing trend in health expenditure. The MAPE value of 5.19% indicates the predictions may err by this amount on either side, thereby justifying the use of the AR(2) autoregressive model as a short-term forecasting tool for CHE_GDP.

Accuracy: The AR model was built using 80% of the data and tested on 20%. Standard Error metrics were used to evaluate the predictions: Mean Absolute Error (MAE) is 0.17, Root Mean Square Error (RMSE) is 0.22, and Mean Absolute Percentage Error (MAPE) is 5.19%.

Forecast with MA models: We figured out the best order for the Moving Average (MA) model by cross-validation with differing values of q. The assessed measure was the Mean Absolute Error (MAE). As shown in the Figure, the outcome MAE figures reduce when increases in value of q, having the least at . Beyond that point severe growth of error happened to indicate the suitability of an MA(4) model in projection for CHE_GDP of India.

Though indicating a satisfactory overall capturing of CHE_GDP in India during the test period (2018-2022), this MA(4) model forecasting accuracy does show some deviations in particular years. These imply that the model, while capturing minor short-term fluctuations, may not be able to capture broader or longer variations or outside shocks to health expenditure. It appears that historically there has been a steady decrease in CHE_GDP, especially from the early 2000s and into 2015, at which point there was a massive decline, again probably because of economic restrictions, policy changes, or instability of funds within the healthcare system; then finally, post-2020, there has been a small but persistent rise, which again will likely be seen as extending by the MA(4) model from 2023-2027. With an MAE of 0.1879, it does indicate a fairly good forecasting accuracy. However, further improvement may happen if more macroeconomic factors such as GDP growth rates, inflation, and health policies, are plugged into the model.

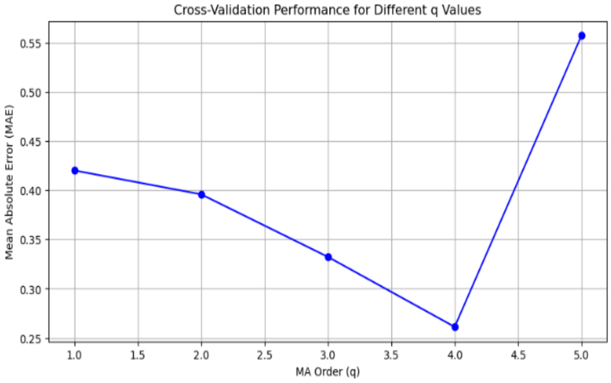

Fig -6: CrossValidation Performance for Different q Values

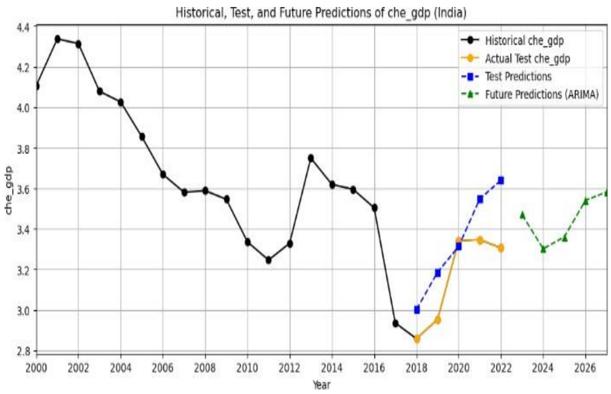

Fig -7: Predictions of India using MA model.

The MA(4) model has been satisfactorily accurate in forecasting CHE_GDP for India. Here are the model evaluation metrics: MAE: 0.1879, RMSE: 0.2134. These figures suggest that the model quite rightly picks up sharp fluctuations in the short term without much overall error.

Forecasting with ARMA Model: The ARMA model trained at optimal parameters of AR (p) = 1 and MA (q) = 1 has been modeled to forecast India's CHE_GDP (Current Health Expenditure as a percentage of GDP). Test year projections (2018-2022) show a very good match with the actuals with respect to short-term variation. Mean Absolute Error was 0.11, with the Root Mean Squared Error was 0.14, indicating that the model performed well in short-term forecasting. Projections for the future years' 2023-2027 suggest that CHE_GDP would grow at a constant rate, which is seen as a recovery trend of the years post-2020.

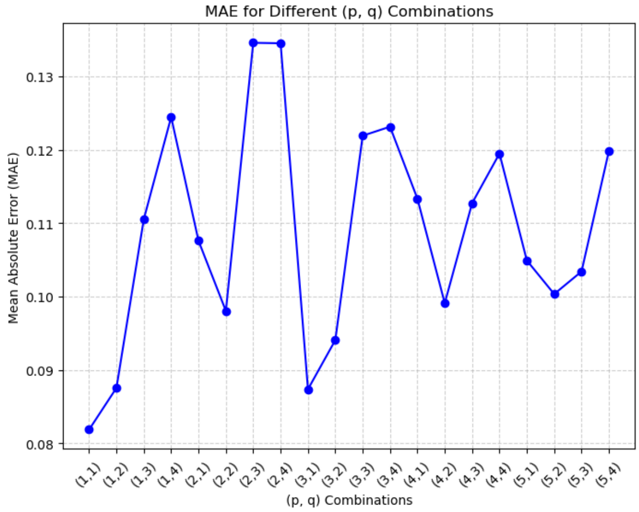

Fig -8: MAE for different (p,q) lags.

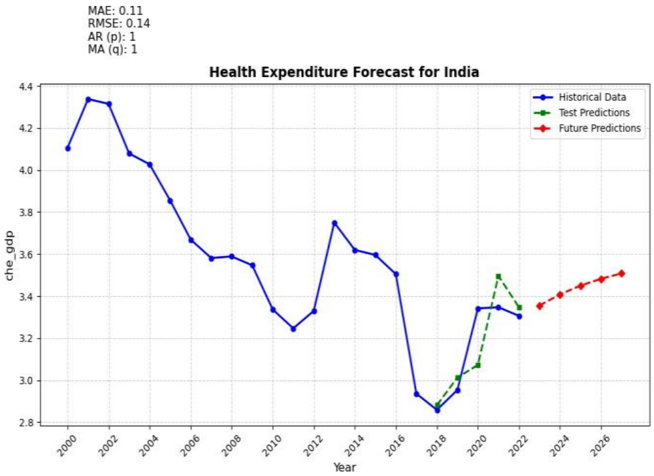

Fig -9: ARMA Predictions for India

The ARMA model captures those short-term dependencies and cycles then falls short of long-term trends and external economic shocks. Rolling statistical analysis and ADF test confirmed the presence of stationarity, hence validating suitability for ARMA time series modeling. Forecast indicates a possible rebound of health expenditure in line with post-pandemic recovery trends.

Forecasting with LSTM(Univariate model): The Long Short-Term Memory (LSTM) univariate model was trained and tested to forecast trends in health expenditure as a percentage of GDP. Training and validation loss curves revealed that the model converged nicely, with little overfitting. There was a steep decline in loss during the initial epochs, which started stabilizing after approximately 20 epochs, as seen on the graph of model loss

The model's predictive power was measured using three key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The findings we obtained are MAE: 0.1485; MSE: 0.0349; RMSE: 0.1868;
Test Loss: 0.0349.

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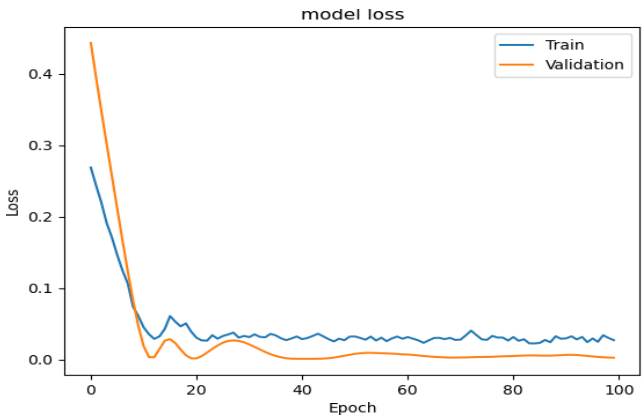

Fig -10: Model loss

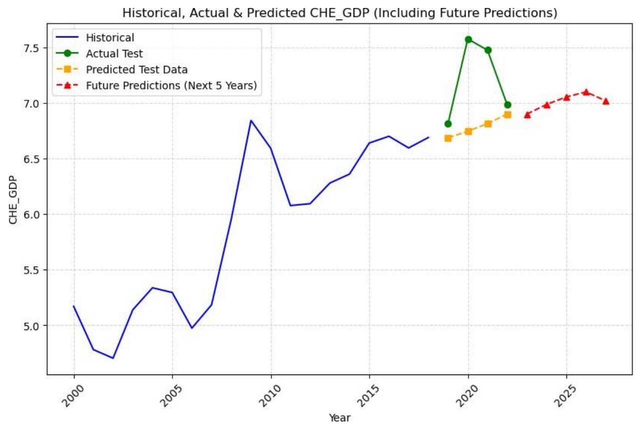

Fig -11: Predictions using LSTM-Univariate Model

Predictions and Trends: The prediction plot shows an illustration of historical values, actual test values, predicted test values, and future predictions for the next five years. The model seems to closely follow the trend of the actual data points, where The model's predictive ability was checked with three major measures: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The results. The future predictions show a level trend, implying a gradual increase in health expenditure concerning GDP going forward.

The inference from these results is that the model has a fairly low error, which indicates that it is probably able to capture the patterns of the given dataset quite well. The model captures temporal dependencies fairly well and gives reasonable forecasts for the future. The very small disparity between training and validation loss indicates good generalization behavior of the model.

Forecasting with LSTM(Multivariate model): Current Health Expenditure as a percentage of GDP (CHE_GDP) was forecasted with the implementation of a multivariate LSTM model. The performance was evaluated against some key metrics; the MAE value measured 0.1226, the MSE at 0.0152, and the RMSE presented a value of 0.1234, which signifies that the model has a good predictive capability. The validation loss was also low, showing the good generalization capability of the model on unseen data.

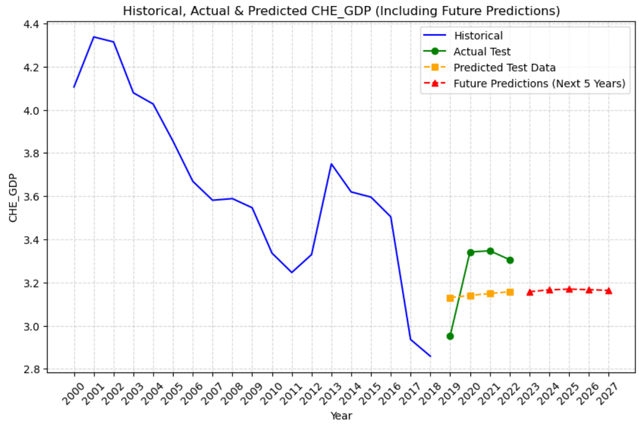

Fig -12: Predictions using LSTM-Multivariate Model-India.

The inversed transformed predictions to the original scale with respect to the actual CHE_GDP values followed very closely in time, especially in the short term. A few initial test predictions of 3.13, 3.14, 3.15, and 3.16 were made against true values of 2.95, 3.34, 3.35, and 3.30, revealing a reasonable approximation, and small deviations. The graphical representation of the historical time series data and the actual test values, along with future predictions, show the model's ability to capture general trends adequately, with minor discrepancies in weighted regions. Predicted next 5 years' values: [3.15723322 3.16604606 3.16923047 3.16709186 3.16314209] for India.

The model shows that CHE_GDP can be reasonably predicted for the next 5 years, pointing to stable or slightly increasing trends in many regions. Nevertheless, it is limited by the inability to simulate external economic shocks, implementing policy interventions, and the pandemic-induced fluxers, thus inducing uncertainty in its long-term prediction.

Table -1: Accuracy Metrics.

Model	Approach	MAE	RMSE
AR	Univariate	1.40	5.63
MA	Univariate	0.5326	0.9601
ARMA	Univariate	0.4553	0.8094
LSTM-Univariate	Deep Learning	1.1469	1.2703
LSTM-Multivariate	Deep Learning	1.1871	1.3048

5. CONCLUSIONS

The study carried out the comparative analysis of traditional time series models and the deep learning-based Long Short-Term Memory (LSTM) models, for the prediction of Current Health Expenditure (CHE) measured as a percentage of GDP (CHE_GDP).

Among the traditional models, ARMA performed well for short-term forecasting.
The LSTM models exhibited variations in error performance. Univariate LSTM performs slightly better than multivariate models, implying that any addition of extra features in this dataset does not seem to improve the performance. The work assumed the stationarity of the timeseries under consideration. However, the data of several countries are nonstationary and have cyclic changes also. It is expected that the performance of both ARMA and LSTM models will improve if seasonal and nonstationary trend effects are removed. Hence the future scope of work must include the techniques that can take care of these effects to produce better short term as well as long term predictions.

REFERENCES

[1] T. Hitiris and J. Posnett, "The determinants and effects of health expenditure in developed countries", *Journal of Health Economics*, vol. 11, pp. 173-181, 1992.

[2] J. P. Newhouse, "Cross-national differences in health spending: What do they mean?", *Journal of Health Economics*, vol. 6, pp. 159-162, 1987.

[3] Global Burden of Disease Health Financing Collaborator Network. Past, present, and future of global health financing: a review of development assistance, government, out-of-pocket, and other private spending on health for 195 countries, 1995–2050. The Lancet. 24 April 2019. doi: http://dx.doi.org/10.1016/S0140-6736(19)30841-4

[4] J. P. McCusker, D. L. McGuinness, J. Lee, C. Thomas, P. Courtney, Z. Tatalovich, et al., "Towards Next Generation Health Data Exploration: A Data Cube-based Investigation into Population Statistics for Tobacco", *46th Hawaii International Conference on System Sciences(HICSS)*, pp. 2725-2732, 2013.

[5] E. Meara, C. White and D. M. Cutler, "Trends in medical spending by age 1963–2000", *Health Affairs*, vol. 23, no. 4, pp. 176-183, 2004.

[6] John Wang, Zhaoqiong Qin, Jeffrey Hsu, Bin Zhou,A fusion of machine learning algorithms and traditional statistical forecasting models for analyzing American healthcareexpenditure,HealthcareAnalytics,Volume5,2024,100312,ISSN27724425,https://doi .org/10.1016/j.health.2024.100312.T.E

[7] A. Burrell, V. Zah, Z. Zrubka, and C. Asche, "PD45 Paying For Digital Health: What Evidence Is Needed?", *Int. J. Technol. Assess. Health Care*, vol. 38, no. S1, pp. S106-S107, Dec. 2022.

[8] Roger Muremyi Prediction of out-of-pocket health expenditures in Rwanda using machine learning techniques

[9] N. Chioma Ewurum and S. Oseloka Okafor, 'Global Health Security: An Evaluation of Public Health Expenditure, Health Status and Economic Development in Nigeria', Sustainable Development. IntechOpen, Jun. 19, 2024. doi: 10.5772/intechopen.114264.

[10] Z. Song, S. Rose, D. G. Safran, B. E. Landon, M. P. Day and M. E. Chernew, "Changes in health care spending and quality 4 years into global payment", *New England Journal of Medicine*, vol. 371, no. 18, pp. 1704-1714, 2014.

[11] Evolution and patterns of global health financing 1995–2014: development assistance for health, and government, prepaid private, and out-of-pocket health spending in 184.

[12] Ntivuguruzwa S (2023) Application of Machine Learning in Long Term Healthcare Cost Prediction in Rwanda. Health Sci J. Vol. 17 No. 4: 1007.

[13] Predicting Health Spending in Turkey Using theGPR, SVR, and DT Models Türkiye Sağlık Harcamalarının GPR, SVR ve DT Modelleri ile

[14] TahminiDrivers of healthcare expenditure growth in West Africa: A panel data investigation Rasaki Stephen Dauda, Fiyinfoluwa Adeyinka Balogun First published: 23 November 2023 https://doi.org/10.100 2 /hpm.3735

[15] FFA Working Paper No. 25,July 2022, authored by Thomas Brändle and Carsten Colombier.

[16] Tetiana Zatonatska, Olena Liashenko, Yana Fareniuk,Oleks and Dluhopolskyi, Artur Dmowski, and Marzena Cichorzews ka."The migration Influence on the Forecasting of Health Care Budget Expenditures in the Direction of Sustainability:

[17] Z. Zrubka et al., "Towards a single goodness metric of clinically relevant accurate fair and unbiased machine learning predictions of health-related quality of life", *2023 IEEE 27th International Conference on Intelligent ystems (INES)*, pp. 000285-000290, Jul. 2023. *Engineering S*

[18] M. Alkhaldi, A. Al Basuoni, M. Matos, M. Tanner, and S. Ahmed, "Health Technology Assessment in High Middle and Low-income Countries: New Systematic and Interdisciplinary Approach For Sound Informed-Policy Making: Research Protocole", *Risk Manag. Health. Policy*, vol. 14, pp. 2757-2770, 2021.

[19] Tracking development assistance for health and for COVID-19: a review of development assistance,

government, out-of-pocket, and other private spending on health for 204 countries and territories, 1990–2050

[20] Samah, I.H.A., Rashid, I.M.A., Husain, WAFW, Ibrahim, S., Hamzah, H., Amlus, M.H., 2020. The impact of healthcare expenditure and healthcare sector growth on CO2 emission using dynamic panel data system GMM estimation model during COVID 19 crisis. Int. J. Energy Econ.Policy10,235–241. https://doi.org/10.32479/ijeep.9769

[21] Zhang, C., Wei, H., Zhao, X., Liu, T., Zhang, K., 2016. A Gaussian process regression based hybrid approach for short-term wind speed prediction. Energy Convers. Manag. 126,1084https://doi.org/10.1016/j.enconman.2016.08.086.