Advanced Industrial SCIence
Vol. 1, No. 1, pp. 7-15, 2022
ISSN 2951-2476
https://doi.org/10.23153/AI-Science.2022.1.1.007

Big Data Management in Structured Storage Based on Fintech Models for IoMT using Machine Learning Techniques

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기계학습법을 이용한 IoMT 핀테크 모델을 기반으로 한 구조화 스토리지에서의 빅데이터 관리 연구

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Abstract To adopt the development in the medical scenario IoT developed towards the advancement with the processing of a large amount of medical data defined as an Internet of Medical Things (IoMT). The vast range of collected medical data is stored in the cloud in the structured manner to process the collected healthcare data. However, it is difficult to handle the huge volume of the healthcare data so it is necessary to develop an appropriate scheme for the healthcare structured data. In this paper, a machine learning mode for processing the structured heath care data collected from the IoMT is suggested. To process the vast range of healthcare data, this paper proposed an MTGPLSTM model for the processing of the medical data. The proposed model integrates the linear regression model for the processing of healthcare information. With the developed model outlier model is implemented based on the FinTech model for the evaluation and prediction of the COVID-19 healthcare dataset collected from the IoMT. The proposed MTGPLSTM model comprises of the regression model to predict and evaluate the planning scheme for the prevention of the infection spreading. The developed model performance is evaluated based on the consideration of the different classifiers such as LR, SVR, RFR, LSTM and the proposed MTGPLSTM model and the different size of data as 1GB, 2GB and 3GB is mainly concerned. The comparative analysis expressed that the proposed MTGPLSTM model achieves ~4% reduced MAPE and RMSE value for the worldwide data; in case of china minimal MAPE value of 0.97 is achieved which is ~ 6% minimal than the existing classifier leads.

Key Words : Big Data, FinTech, Structured Storage, Outlier model, machine learning, linear regression

요 약 사물인터넷(IoT) 기술은 최근 의료사물인터넷(IoMT)으로 정의된 대량의 의료 데이터를 처리하여 발전을 위해 개발된 의료분야에서 많이 활용되고 있다. 수집된 광범위한 의료 데이터는 수집된 의료 데이터를 처리하기 위해 구조화된 방식으로 클라우드에 저장된다. 그러나 방대한 양의 의료 데이터를 효과적으로 처리하는 것은 쉽지 않기 때문에 의료분야 구조 데이터를 개발하는 것이 필요하다. 본 논문에서는 IoMT에서 수집된 구조화된 건강 관리 데이터를 처리하기 위한 기계 학습 모드를 개발하였다. 광범위한 의료 데이터를 처리하기 위해 본 논문에서는 의료 데이터 처리를 위한 MTGPLSTM 모델을 제안하였다. 제안된 모델은 의료 정보 처리를 위한 선형 회귀 모델을 통합한다. 개발된 모델 이상치 모델은 IoMT에서 수집된 COVID-19 의료 데이터들의 평가 및 예측을 위해 FinTech 모델을 기반으로 구현되었다. 제안된 MTGPLSTM 모델은 감염 확산 방지를 위한 계획 계획을 예측하고 평가하기 위한 회귀 모델로 구성된다. 개발된 모델 성능은 LR, SVR, RFR, LSTM 및 제안된 MTGPLSTM 모델과 같은 서로 다른 분류기를 고려하였으며 1GB, 2GB, 3GB 등 데이터 크기가 다르다는 점도 주요하게 고려되었다. 제안된 MTGPLSTM 모델이 전 세계 데이터에 대해 최대 4% 감소된 MAPE 및 RMSE 값을 달성하였고 중국의 경우 기존 분류기보다 최대 6% 최소인 최소 MAPE(0.97)이 달성되었다.

주제어 : 빅데이터, 핀테크, 구조화 스토리지, 이상치 모델, 기계학습

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Received August 23, 2022 Revised September 7, 2022
Accepted September 23, 2022 Published September 28, 2022

1. Introduction

Globally, the Internet of Things (IoT) is emerging technology widely accepted for the attainment of the immense power and capability for any time, network, anyplace or service [1]. IoT provides the superpower next-generation machinery those impact highly on the present business spectrum for the industries or researchers in the possible development solution [2]. The IoT provides the interaction of the smart devices and objects with the existing infrastructure with efficient utilization of the resources with significant advantage in the provision of the services and the intelligent systems [3]. The interaction is beyond the limit of the Machine-to-machine interaction with the serial connectivity between the network devices for the extreme service provision [4]. IoT has been broadly utilized in the different applications such as congestion control, solution for smart cities, security, structural health, management of waste, retails, smart healthcare, logistics and industrial control for the smart solution [5].

Among different applications healthcare is highly influencing termed as the IoMT (Internet of Medical Things) instead of replacing the traditional system to call doctor. In conventional system neither doctor nor hospitals does not track the health status of the patients even that is also not possible. With the implementation of the IoMT it facilitates the patient monitoring and self-monitoring [6]. With IoMT doctor delivers the excellent care and support to the patient with the effective tracking of the health status. Based on the tracked patient health status through significant strategies and make precautions accordingly. With IoMT the interaction between doctor and patients are efficient with massive growth to achieve the patient satisfaction and engagement [7]. Through health monitoring system patient can reduces the hospital stay lifetime and reduce the cost. The IoMT increases the quality of the treatment and prevents the patient re-admission in the hospital. As the IoMT exhibits the significant role towards healthcare industry for the device expanding and interaction with the people effectively. IoMT comprises of the different applications those are beneficial for the hospital, patient and doctors. IoMT comprises of the wearable devices such as fitness band, smart watches and other wireless-enabled devices [8]. The devices in the IoMT utilized for the different health monitoring such as blood pressure, heart rate, glucometer and so on. With the design of the effective intelligent devices gradual impact on the patient health status are monitored. In case of emergency scenario, the patient information are forwarded to the doctors and other family members. IoMT devices collects the information about the patient are circulate to the family members through the smart-enabled devices for anytime and anywhere services[9]. The collected information are processed and evaluated by the doctor and hospitals those are stored and monitored. The data collected from the IoMT devices are stored in cloud termed as Big data. Big data required structured analysis for the monitoring the patient information.

Big data and big data analytics are the effective decision making process for the prediction comprises of the big data, big data architecture and data stock market [10]. The big data were comprises of the 5v's for the data processing with the effective tools and techniques. Financial analytics with the shareholders provides the creation value, equity market, characteristics of the financial analytics and information technology. Financial analytics comprises of the information technology for the equity market for the sample investment strategies for the financial analytics and shareholders with the structured big data model to achieve the decision making process [11]. Through implementation of the big data integrated with the financial technology exhibits the significant solution for the equity market. Based on the effective performance the big data for the healthcare is evaluated and analyzed.

Data collected form the IoMT are processed for the prediction and generation for the monitoring of the healthcare information. With the big data analytics in the healthcare information data were distinguished with the agencies in their own format [12]. Based on current scenario, big data architecture with the FinTech model divided in to three parts such as News, information and prediction[13]. The data sources are identified based on the required sources for the market future prediction with the stored, acquired and processed heterogeneity of the data. However, the IoMT model comprises of the temporal data which is challenging in the dig data processing for healthcare applications. Finally, the big data analytics model comprises of the architecture for the analyze, visualize, decision reporting and generated data for processing. In the present scenario, the required cost is not affordable for the data by the investor with effective resource management[14].

2. Related Works

IoT architecture for the medical application comprises of the sensor data for the data transmission to the cloud through the gateway. The Internet of Medical Things (IoMT) model is also known as healthcare IoT for the vast range of applications. IoMT model has been adopted in the effective remote patient health monitoring for the health parameter monitoring. In [14] proposed a IoT cloud communication for the direct transmission of the ECG signal through WiFi for the practical and well connected regions of urban area. For effective data transmission in [15] described the healthcare monitoring system for the end-to-end communication with the selective link protocol transmission for the identification of the best path to the IoT gateway with the nearest cloud center. In [16] developed a cross-layer optimization model for the physical, link and network layer communication for the reliable and improved transmission with the improved lifetime of the battery in the area network.

In [17] proposed an ultra-low power ECG node mover estimation with the embedded smart phone to capture the ECG signals for the continuous monitoring of the patient. In [18] developed a IoMT system for the spoke model with the computation of the sensor node, hub and WiFi gateway for the processing. In [19] presented a research mechanism for the mobility and activity detection in the fusion sensor network for the increased data integrity and efficiency with implemented body-worn sensors. The developed scheme is effective for the remote monitoring system for the non-exhaustive model based on the data priority model. In [20] evaluated the solution and challenges to evaluate the environment energy and bandwidth model for the rural region monitoring. In [21] proposed a hybrid sensing network for the smart hospital environment for the low-power wireless personal area network integrated with the radio frequency identification (RFID)to capture the environment parameters for the patients.

3. Proposed Model

In a real-time scenario, the machine learning model is processed with the effective structured big data model using the FinTech model. The proposed scheme GPRLSTM model designed based on the consideration of the dataset, methodology, model and statistical analysis. The developed

GPRLSTM model utilizes the Gaussian Process Regression (GBR) non-parametric regression model for the predictive analysis. The proposed MTGPLSTM model comprises of the complex arbitrary system model for the Multi-Task Gaussian Process Regression (MTGP). This paper proposed an MTGPLSTM model integrated with the GPR for the prediction of the COVID-19 outbreak based on the structured big data model. The structured big data model comprises of the time series prediction with the processing of the input and output data based on the reference series. The MTGPLSTM model comprises of the time series model for the testing and training mechanism without kernel matrix. Through the MTGPLSTM model output tasks are processed based on the consideration of the two cases. In figure 1 presented the process involved in the IoMT data collection process for the COVID-19.

The standard GPR model utilized for the proposed MTGPLSTM model is presented in equation (1)

$$s = f(c) \sim M(m(c), i(c, c')) \tag{1}$$

In above equation (1) mean function is denoted as $m(c)$ and latent variable is denoted as $f(c)$. The covariance function is denoted as the $i(c, c')$.

The proposed MTGPLSTM squared exponential kernel (SEK) is denoted as in equation (2).

$$k_{sek} = \theta_1^2 \exp\left(-\frac{c^2}{\theta_2^2}\right) \tag{2}$$

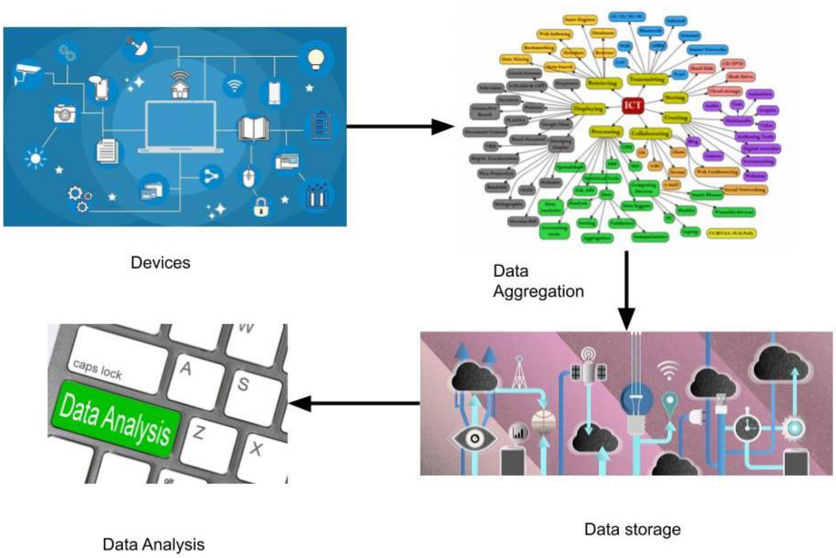

Fig. 1. IoMT processing for COVID-19

Where, c represented the Euclidean distance and the hyper-parameters are denoted as θ_1, θ_2 for the optimized model. The proposed MTGPLSTM model comprises of the kernel matrix I with the hyper-parameters those are estimated based on the minimization of the NLML (Negative Log Marginalized Likelihood) as shown in equation (3)

$$NLML = -\log(p(a|c, \theta)) \tag{3}$$

The proposed MTGPLSTM model comprises of the regression model as stated in the equation (4)

$$\begin{pmatrix} a_r \\ a_p \end{pmatrix} = N\left[0, \begin{pmatrix} \theta_{rr} I(b_r, b_r) & \theta_{rp} I(b_r, b_p) \\ \theta_{pr} I(b_p, b_r) & \theta_{pp} I(b_p, b_p) \end{pmatrix}\right] \tag{4}$$

Based on the consideration of the variable the proposed MTGPLSTM model matrix is computed as in equation (5)

$$\begin{pmatrix} a_r \\ a_p \end{pmatrix} = N(0, I_{MTGPLSTM}(b_r, b_p)) \tag{5}$$

Where, vector for two input and output dimensionality is denoted as a_r, a_p, b_r and b_p. With 1D the time series vector is represented as b_r and b_p. The output series correlation coefficient of the variables are denoted as θ_{rr}, θ_{pr}, θ_{rp} and θ_{pp}. The computation of the vector for the proposed MTGPLSTM model is presented in equation (6)

$$F_p^* = I_{MTGPLSTM}(b, b_p^*)(I_{MTGP}(b_r, b_p)) + \sigma_n^2 J)^{-1} \begin{pmatrix} a_r \\ a_p \end{pmatrix} \tag{6}$$
$$= X_{MTGPLSTM} \begin{pmatrix} a_r \\ a_p \end{pmatrix}$$

Where,

$$I_{MTGPLSTM}(b, b) = \begin{pmatrix} \theta_{rr} I(b_r, b_r) & \theta_{rp} I(b_r, b_p) \\ \theta_{pr} I(b_p, b_r) & \theta_{pp} I(b_p, b_p) \end{pmatrix}_{(r+p)\times(r+p)}$$

$$I_{MTGPLSTM}(b, b_p^*) = \theta_{pr} I(b_p^*, b_r) \theta_{pp} I(b_p^*, b_p)_{15\times(r+p)}$$

The process of the proposed MTGPLSTM model for the computation of the factors involved in the structured big data for the COVID-19 is presented.

The algorithm for the proposed MTGP for COVID-19 outbreak forecasting has been deliberated below in Fig. 2.

Algorithm 1 : Improved MTGP model for structured big data
Step 1: Initialize the COVID-19 dataset for the time chunk $l$and a_r, a_p, b_r, $b_p$as $b_r = \{T_{t-l}, \ldots, T_t, \ldots, T_{t+15}\}$, $b_p = \{T_{t-l}, \ldots, T_t\}$, where $a_r \in R^{r\times 1}$ are utilized for processing the structured data related to COVID-19 for the time b_r, $a_p \in R^{p\times 1}$
Step 2: Compute the MTGPLSTM using the equation (4) with the estimation of the kernel hyper parameters θ_{rr}, θ_{pr}, θ_{rp} and θ_{pp}. The reduced NLNL model comprises of the optimal hyper-parameter estimation.
Step 3: Compute the predictive distribution with the MTGPLSTM
Step 4: Evaluate the transmit time $t+1$ for every step 1 to 3

Fig. 2. Improved MTGP model for structured big data

The proposed MTGPLSTM model comprises of the regression mode to perform predictive analysis. The developed model uses the linear regression model with the consideration of the two variable one is dependent and another model is explanatory or descriptive variable. The linear regression model evaluates the relationship between the variables in the data those are denoted in the slope. The linear regression (LR) model for the line in the slope is presented in equation (7) defined as the line slope b and the y-intercept is denoted as a, the dependent variable with the reliant variable is represented as y and the variable x denoted as the descriptive or explanatory variable. The mathematical formulation of the linear regression model is defined as in equation (7)

$$y = a + bx \tag{7}$$

The equation (8) and (9) the calculation is defined as follows:

$$b(slope) = \frac{n\sum xy - (\sum x)(\sum y)}{n\sum x^2 - (\sum x)^2} \tag{8}$$

$$a(\text{intercept}) = \frac{\text{n}\sum \text{y} - \text{b}(\sum \text{x})}{\text{n}} \tag{9}$$

With predictive analysis the commonly used regression model comprises of the SVR model presented in equation (10) and (111)

$$f(x) = \omega\phi(x) + b \tag{10}$$

$$\varnothing : R^n \rightarrow F, \omega \in F \tag{11}$$

Where, the ϕ represents the feature space in high dimensions and the coefficient $\phi(x)$ defines the variables ω and b as presented in equation (12)

$$\begin{aligned} R_{SVR}(c) &= R_{emp} + \frac{1}{2}\|\omega\|^2 \\ &= c \times \frac{1}{n}\sum_{i=1}^{n} L_{\epsilon}(d_i, y_i) + \frac{1}{2}\|\omega\|^2 \end{aligned} \tag{12}$$

Where, the empirical risk assessment in the COVID-19 is represented as R_{emp}, the $\|\omega\|^2$ denoted the Euclidian norms, the empirical error is represented as $c \times \frac{1}{n}\sum_{i=1}^{n} L_{\epsilon}(d_i, y_i); i = 1$ and the cost of the empirical risk is represented as c. The big data structure for the analysis is presented in equation (13).

$$L_{\epsilon}(d, y) = \begin{cases} |d - y| - \epsilon & |d - y| \geq \epsilon \\ 0 & otherwise \end{cases} \tag{13}$$

In above equation (13), the estimated loss function is denoted as in equation (14) and (15).

$$R_{SVR}(\omega, \text{Ɽ}^{*x}) = \frac{1}{2}\|\omega\|^2 + c \times \frac{1}{n}\sum_{i=1}^{n}(\text{Ɽ}_i, \text{Ɽ}^{*x}) \tag{14}$$

$$d_i - \omega\phi(x_i) - b_i \leq \epsilon + \exists_i \tag{15}$$

Subjected to,

$$\omega\phi(x_i) + b_i - d_i \leq \epsilon + \exists^* \exists^* \geq 0 \tag{16}$$

In testing phase of error minimization the above equation (16) is considered for the slack variable for the ups and downsides represented as $\exists$ and $\exists^*$. The proposed MTGPLSTM model mathematical model formulation is presented for the input gate as presented in the equation (17)

$$i_t = \sigma(W_i x_t + X_i h_{t-1}) \tag{17}$$

Where, σ represents the sigmoid function, the X_i previous unit output is represented as h_{t-1} and weight matrix is denoted as W_i. The LSTM model for gate is denoted in equation (18)

$$f_t = \sigma(W_0 x_t + X_0 h_{t-1}) \tag{18}$$

Where, σ represents the sigmoidal function, the previous unit cell is denoted as h_{t-1} and the weighted matrix is denoted as W_0. The memory cell in the LSTM is presented in equation (19).

$$\tilde{c_t} = \tanh(W_c x_t + X_c h_{t-1}) \tag{19}$$

In above equation (20), the previous unit output is denoted as h_{t-1} and the weighted matrix is represented as W_c. The final memory cell is denoted as in equation (20).

$$c_t = f_t \times \widetilde{c_{t-1}} + i_t \times \tilde{c_t} \tag{20}$$

In the above equation (21) the forget gate is represented as $f_t \times \widetilde{c_{t-1}}$, the $t-1$ cell state is denoted as c_t for the time t-1 and t respectively. The output final equation is represented in equation (21).

$$h_t = o_t \times \tanh(c_t) \tag{21}$$

Where, the variables o_t and c_t denotes the output or exposure gate in the final memory cell, respectively.

Algorithm 2 : Outlier Detection for IoMT dataset

Global variables: epsilon = 5; minpts =10;

1. Load dataset collected from IoMT *P*.
2. *D = Read the collected data*
3. for each i evaluate the data P do
4. d_{ij} = the distance between the variable i and j
5. end for
6. end for
7. compute the epsilon distance for each points as C_i
8. Compute (i, C_i)
9. end procedure
10. procedure minimize $(key\ i,\ erate\ the\ every\ data\ points \in the\ \epsilon\ as\ C_i)$
11. if $|C_i| > \min pts$ then
12. is core point = True
13. M+ = (C_i)
14. else
15. is core point = False
16. end if
17. for every point i and C_i do
18. $\sum_i + \ = distance\ between\ i$ and j
19. end for
20. $outlier\ score = 1/\sum\ _i$
21. $emit(i,\ OutlierScore)$
22. end procedure

Fig. 3. Outlier Detection for IoMT dataset

4. Results and Discussion

The proposed MTGPLSTM model evaluated for the hyperparameter settings and examined for the experimental evaluation setting. The simulation setting comprises of the different parameters such as prediction model, hyperparameters, selection of parameters and best hyperparameters. In table 1 presented the experimental evaluation of the hyperparameter setting with the hyper-tuned model for the determination of the selection criteria in the proposed model, the experimental evaluation of the hyper-tuned parameters is presented

Table 1. Hyperparameter Selection

Prediction Model	Hyperparameter	Parameter Selection	Hyperparameter Used
LR	Dual	[True, False]	False
	max_iter	[100,110,120,130,140]	100
	C	[1,1.5,2,2.5]	2
SVR	Kernel	Rbf	Rbf
	C	[0.1, 1, 100, 1000]	100
	Gamma	[0.0001,0.001,0.01, 0.005,	0.1
	Epsilon	[0.0001,0.001,0.01,0.05,	0.0001
RFR	Bootstrap	[True, False]	True
	max_depth	[10,20,30,40,50,60,70,80,	70
		90,100,None]	
	max_features	['auto','sqrt']	Auto
	min_samples_leaf	[1, 2, 4]	4
	min_samples_split	[2, 5, 10]	10
LSTM	Neurons	[1, 2, 3, 4, 5]	1
	Batches	[1, 2, 4]	4
	Epochs	[500,1000,2000,4000,6000]	1000

4.1 Model Performance Evaluation

In table 2 presented a results for the regression model to evaluate the COVID-19 outbreak. The examination is based on the consideration of the five parts. Initially, the forecasting is evaluated based on the consideration of the confirmed cases related to COVID-19. The examination is based on the consideration of the country specific parameters such as China, India, Italy, and USA. The evaluation of the proposed MRGPLSTM model comprises of the information collected from the different countries such as China, India, Italy and USA. The performance of the developed model is evaluated based on the consideration of the MAPE and RMSE value. In table 2 presented the comparative analysis of the proposed MRGPLSTM throughout the world is presented.

Table 2. Comparison of Worldwide

Method	Prediction with the structured Data					
	1GB		2GB		3GB	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
LR	7.22	2092.62	6.68	2102.23	6.75	2199.38
SVR	3.65	465.50	6.78	483.85	3.67	596.73
RFR	6.80	1763.68	6.43	1792.45	6.44	1863.73
LSTM	2.06	293.67	2.86	324.67	2.65	459.78
MTGPLSTM	1.16	123.76	1.27	167.83	1.45	329.36

The examination of the data expressed that the proposed model exhibits the minimal MAPE and RMSE values. The performance of the proposed MRGPLSTM model is evaluated based on the consideration of the calculated metrics for the estimation of the COVID-19 variables. The experimental analysis is considered based on the prediction of the different features with the different datasets 1GB, 2GB and 3GB. The table 2 the proposed MTGPLSTM model compute the MAPE and RMSE value based on the consideration of the different features for the analysis. Based on the similar pattern of the information the data related to COVID are collected and evaluated for the other countries as presented in table 3.

Table 3. Comparison of China

Method	Prediction with the structured Data					
	1GB		2GB		3GB	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
LR	3.5	688.21	3.57	713.79	3.81	723.6
SVR	1.50	220.92	1.56	241.42	1.78	286.25
RFR	2.60	457.70	2.58	461.93	2.68	513.27
LSTM	1.10	178.93	1.19	198.24	1.28	213.67
MTGPLSTM	0.97	128.34	0.978	143.79	1.06	178.24

In table 4 the comparison of the IoMT information from India for the varying file size of 1GB, 2GB and 3GB is presented.

Table 4. Comparison of India

Method	Prediction with the structured Data					
	1GB		2GB		3GB	
	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
LR	7.23	1605.34	7.41	1657.43	7.58	1678.45
SVR	2.78	376.34	3.24	413.56	3.48	456.46
RFR	5.35	1456.73	5.37	1456.76	4.6	1568.46
LSTM	2.09	276.47	2.18	276.54	5.3	328.46
MTGPLSTM	1.17	179.25	1.32	187.34	1.56	223.47

5. Conclusions

The developed model comprises of the GPR model integrated with the machine learning based LSTM architecture. Within the LSTM model outlier model based FinTech is implemented for the vast range of dataset size 1GB, 2GB and 3GB. The performance of the proposed MTGPLSTM model is evaluated for the different classification model Linear Regression(LR), Random Forest Regression(RFR), Support Vector Regression(SVR), and Long Short-Term Memory (LSTM) with our proposed MTGPLSTM for suitability correctness analysis. The performance of the proposed MTGPLSTM model is evaluated based on the consideration of the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) for the varying size of data 1GB, 2GB and 3GB data. The comparative analysis expressed that the proposed MTGPLSTM model achieves the minimal MAPE and RMSE value for the COVID-19 dataset of worldwide, China and India. The proposed model exhibits the ~ 4% reduced MAPE value for the worldwide dataset. With the county wise analysis the achieved MAPE value is computed as 0.97 and 4.12 for Worldwide, China, India. The analysis expressed that the value is ~ 4% - 6% minimal RMSE value than the conventional classifier. In future the developed model is evaluated based on the consideration of the different dataset with the boosting technique to increase the model efficiency.

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