Research On Urban Traffic Flow Prediction Based On Deep Recurrent Network And Bidirectional LSTM

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Traffic flow (TF) forecasting plays a crucial role in modern urban transportation systems by enabling congestion mitigation and efficient traffic management. With the rapid growth of intelligent transportation systems, robust prediction models are required to process large-scale traffic data in real time. This study presents an enhanced urban traffic forecasting model based on Deep Recurrent Networks (DRN) integrated with Bidirectional Long ShortTerm Memory (BiLSTM) networks to effectively capture temporal dependencies and spatial correlations in traffic data. Traffic datasets collected from sensors at major intersections include vehicle counts, speed, and congestion information across peak and off-peak periods. Noise reduction is performed using median filtering, followed by Min-Max normalization. Wavelet transform-based feature extraction captures multi-resolution traffic patterns. The proposed Malleable Aquila Optimized DRN-BiLSTM model achieves superior performance, attaining an R^2 of 0.97 , RMSE of 12.14, and MAE of 10.04, demonstrating its effectiveness for shortterm urban traffic forecasting and planning.

Keywords: Urban Traffic Flow, Intelligent Transportation Systems, Malleable Aquila Optimized-DRN with BiLSTM, Traffic Management, Predictive Model

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1. Introduction

Traffic congestion in urban cities is a major issue, impacting quality of life, emissions, and economic performance as populations grow and urban areas expand [1]. It leads to wasted time, increased energy consumption, and higher risks of accidents and pollution. Forecasting traffic patterns is crucial for improving traffic control, reducing density, and enhancing mobility across cities [2]. TF forecasting estimates vehicle traffic through road networks over short and long-time horizons, using data from traffic sensors, historical records, and simulation models. This helps decision-makers adjust routes, traffic signals, respond to accidents, and plan infrastructure [3]. Initially, TF forecasting relied on simple statistical models, providing approximate traffic conditions through equations like flow density or flow speed [4].

TF prediction has evolved with data-driven methods, using ML and AI algorithms to leverage large datasets from sensors and GPS devices [5]. These algorithms improve accuracy by considering factors like past traffic data, weather, time of day, and special events [6]. Urban traffic systems are dynamic, with fluctuating demand, weather, incidents, and driver behavior creating uncertainty. Traditional models struggle with this complexity. The MA-DRNBiLSTM framework addresses these challenges by combining bidirectional learning and adaptive optimization, capturing complex relationships and adjusting to changing traffic conditions. The TF in urban areas varies with factors like time of day, day in the week, weather, road construction, traffic accidents, bus schedules, and the state of mind of the drivers [7]. These considerations make predictive models complex and therefore must incorporate highdimensional capabilities to deal with a large amount of data [8].

Accurate traffic flow prediction in urban areas offers several advantages, including effective congestion management, optimized route planning, improved utilization of transportation infrastructure, reduced travel time, and enhanced support for intelligent transportation systems. Accurate traffic predictions enable dynamic traffic control, optimizing routes and signal management, which enhances efficiency, reduces congestion, and shortens travel times [9]. It also aids in infrastructure planning, directing resources to high-traffic areas [10]. The MA-DRN-BiLSTM model forecasts urban traffic by capturing both temporal and geographical data connections. An intelligent planning framework for urban drainage systems, incorporating road network structures for infrastructure optimization [11]. Accurate urban traffic predictions are crucial for city development and transportation policy, helping planners identify congestion-prone areas, forecast traffic demand, and prioritize infrastructure improvements like road expansions and public transit.

1.1. Contributions

- The urban TF data was obtained from the Kaggle platform.
- To enhance the quality, the data is being pre-processed, median filtering is used to remove noise in the data while for normalization of data, Min-max scaling technique is used which ensures the traffic data is clean and normalized for TF prediction.
- The model was able to capture complex patterns and improve input characteristics' predictability by using the wavelet transform to analyse multi-resolution structures from traffic time series.
- The study presented an innovative MA-DRN-BiLSTM model that successfully captures temporal and geographical relationships in traffic data to forecast the urban TF with accuracy.

The remaining portion of the research is structured as follows: Section 2 - Theory and Formula, Section 3 - Experimental Setup, Section 4 - Result and discussion, and Section 5 - Conclusion.

2. Theory and formula

Using past traffic data, research [12] proposed an FDL approach based on the FedSTN algorithm, demonstrating its superiority over traditional methods in forecasting traffic patterns. In [13], a GAGC approach using spatial-temporal graph attention outperformed conventional methods. Research [14] introduced Bi-STAT for precise traffic prediction, showing its advantages and the effectiveness of its components through comprehensive trials. Adaptive traffic management was enhanced in [15] through ML and DL methods, with the MPR model showing superior performance and faster training. Research [16] introduced a hybrid traffic forecasting system combining SAE and LSTM, demonstrating excellent accuracy in representing actual traffic patterns [17].

A spatial-temporal dynamic graph neural network for crowd movement prediction outperformed traditional and DL techniques [18]. The attention-based CNN-LSTM approach [19] showed superior accuracy in traffic flow forecasting, while a DL-based LSTM model for flash crowding in urban areas outperformed traditional methods [20]. The hybrid AAM-DL framework [21] excelled in short-term predictions, capturing complex traffic patterns, and DHSTNet [22] outperformed traditional methods for forecasting crowd movements. The MHSRN model [23] excelled in mean absolute error for region-based forecasting, while STGAT [24] and T-MGCN [25] showed better performance by combining temporal, geographical, and semantic relationships. A DL-based forecasting system [26] further improved traffic predictions.

2.1. Problem statement

Urban traffic jams are a growing issue, impacting quality of life and the economy by increasing travel times, fuel consumption, and pollution. Traditional traffic management systems struggle with urbanization challenges and dynamic traffic patterns influenced by factors like road construction, accidents, weather, and varying vehicle volumes. Conventional models lack scalability and flexibility, particularly in diverse urban areas.

3. Experimental setup

Urban TF data was collected from Kaggle and pre-processed using median filtering for noise removal and Min-max scaling for normalization. Key features were extracted using the Wavelet transform, and the MA-DRN-BiLSTM model was introduced to improve prediction accuracy. The BiLSTM layers in the MA-DRN-BiLSTM model capture both past and future traffic patterns, enhancing accuracy. By integrating DRN for long-term dependencies and MA for real-time adjustments, the model improves stability, particularly during peak hours and fluctuations, outperforming linear models like ARIMA. Fig. 1 displays the overview of the MA-DRN-BiLSTM model.

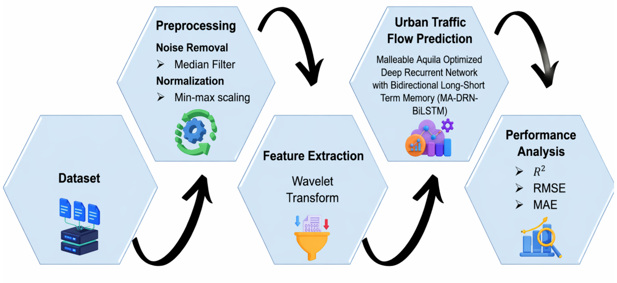

Fig. 1. Overall flow of MA-DRN-BiLSTM approach

Data collection

The urban TF data was gathered from the Kaggle source https://www.kaggle.com/datasets/ziya07/urban-traffic-flow-dataset. This dataset includes temporal, geographical and category information that are important for the perspectives of traffic and is used for predicting the TF in urban area. It contains data on vehicle numbers, flow rates, and traffic jams during various times of the day across several routes and traffic signals installed with sensors. This information might help to examining transportation structures and concerning the design and effectiveness of urban areas. The proposed framework combines traffic flow variables with weather conditions, improving prediction accuracy by accounting for their impact on traffic dynamics. The MA-DRN-BiLSTM model enhances reliability by incorporating environmental factors like reduced speeds and increased congestion.

3.1. Median filter

A median filter replaces a pixel's value with the median of its neighbors, reducing noise and smoothing traffic patterns. The calculation is shown in Eq. (1).

$$e(w,z) = m\,\text{median}_{(t,s)\in T_{wz}}\{h(t,s)\} \tag{1}$$

The median filtering step improves traffic flow prediction by removing impulsive noise and outliers caused by faulty sensors or sudden measurement errors, while preserving important traffic trend transitions.

3.2. Min-max scaling

Min-max scaling alters specific characteristics to a certain fixed scale, often [0,1], for the normalization of data on traffic in cities. The following Eq. (2) is used to normalize each attribute Wj in the conventional Min-Max scaling.

$$Wj' = \frac{Wj - W\min}{W\max - W\min} \tag{2}$$

Min-Max scaling ensures that heterogeneous traffic features such as vehicle count, speed, occupancy, and weather-related variables are normalized to a common range, preventing features with larger magnitudes from dominating the learning process.

3.3. Wavelet transforms

The scaling function and associated wavelet function are denoted by $\phi(s)$ and $\phi(s)$, respectively, and both of them reach the dilation equations, with $\phi_m^n(s)$ and $\phi_m^n(s)$ serving as their translations and dilations in Eq. (3) and Eq. (4).

$$\phi_m^n(s) = 2^{-\frac{n}{2}}\phi\left(2^{-\frac{n}{2}}s - m\right), m \in Y \tag{3}$$

$$\phi_m^n(s) = 2^{-\frac{n}{2}}\varphi\left(2^{-\frac{n}{2}}s - m\right), m \in Y, m \in Y \tag{4}$$

Let us represent a PC using parametric dimensions that are clockwise orientated in Eq. (5).

$$D(s) = \begin{bmatrix} w(s) \\ z(s) \end{bmatrix}, s(k) = \frac{k}{K}, 0 \le k \le K \tag{5}$$

Using the parameterized dimensions and the wavelet transformations, it could derive, in Eq. (6) .

$$\begin{bmatrix} w(s) \\ z(s) \end{bmatrix} = \begin{bmatrix} w_b^N(s) \\ z_b^N(s) \end{bmatrix} + \sum_{n=N-n0}^{N} \begin{bmatrix} w_c^n(s) \\ z_c^n(s) \end{bmatrix} \tag{6}$$

$$w_b^N(s) = \sum_m b_m^N \phi_m^N(s), \quad z_b^N(s) = \sum_m d_m^N \phi_m^N(s) \tag{7}$$

Eq. (7) are referred to as the scale n specified signals.

The relationship between input features like traffic volume, road occupancy, and weather is crucial for traffic flow prediction. Malleable Aquila Optimization reduces redundancy through normalization and feature extraction, improving efficiency and preventing overfitting.

3.4. Malleable Aquila Optimized-DRN with BiLSTM (MA-DRN-BiLSTM)

The suggested MA-DRN-BiLSTM method has shown an innovative way of modeling and forecasting the complex TF in urban city areas. The MA-DRN-BiLSTM model captures nonlinear, time-dependent urban traffic flow, addressing limitations of LSTM and GRU. It uses Malleable Aquila Optimization for adaptive hyperparameter adjustment, improving performance in dynamic conditions. The model combines bidirectional learning and optimization to maintain accuracy during disruptions like accidents and congestion. Algorithm 1 shows the pseudo code for MA-DRN-BiLSTM.

4. Algorithm 1: ma-drn-bilstm

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import (
    LSTM,
    Bidirectional,
    Dense,
    Dropout
)
from aquila_optimizer import AquilaOptimizer
from sklearn.model_selection import train_test_split


def load_data():

    inputs = normalize_data(
        load_traffic_data(),
        load_weather_data(),
        load_road_occupancy_data()
    )

    return train_test_split(
        inputs,
        test_size=0.2
    )


def build_model(input_shape):

    model = Sequential([

        Bidirectional(
            LSTM(units,
            return_sequences=True),
            input_shape=input_shape
        ),

        Dropout(dropout_rate),

        Bidirectional(
            LSTM(units)
        ),

        Dropout(dropout_rate),

        Dense(
            1,
            activation='linear'
        )
    ])

    model.compile(
        optimizer='adam',
        loss='mse'
    )

    return model


def train_and_optimize(model, train_data):

    optimizer = AquilaOptimizer(
        model,
        train_data
    )

    return optimizer.optimize()


def main():

    train_data, test_data = load_data()

    model = build_model(
        input_shape=(
            train_data.shape[1],
            train_data.shape[2]
        )
    )

    optimized_model, _ = train_and_optimize(
        model,
        train_data
    )

    optimized_model.fit(
```

```
        train_data,
        epochs=epochs,
        batch_size=batch_size,
        validation_data=test_data
    )

    print(
        f"Test loss: "
        f"{optimized_model.evaluate(test_data)}"
    )

    future_data = load_future_data()

    print(
        "Predicted traffic flow: ",
        optimized_model.predict(future_data)
    )


if __name__ == "__main__":
    main()
```

4.1. DRN

DRNs predict traffic patterns by capturing temporal relationships in traffic data, using past traffic flow (TF) data, pattern recognition, and real-time projections for efficient traffic management. Unlike traditional neural networks, DRNs retain previous computations, with each layer's output relying on prior layers. In this instance Eq. (8).

$$g_s = e\left(g_{s-1}, W_s\right) \tag{8}$$

4.2. BiLSTM

BiLSTM models capture temporal correlations from both past and future data, improving traffic flow prediction in urban areas. The definition and explanation of an LSTM unit are as follows, Eq. (9).

$$j_s = \sigma\left(V_j \cdot w_s + X_j \cdot g_{s-1} + a_j\right) \tag{9}$$

The IG chooses which data from the prior unit has to be modified.

$$p_s = \sigma\left(V_p w_s + X_p g_{s-1} + a_p\right) \tag{10}$$

$$g_s = p_s \odot \tanh\left(d_s\right) \tag{11}$$

Eq. (10) calculates the OG p_s. Eq. (11) shows that g_s is the LSTM unit's output.

The output layer z_s in the BiLSTM is composed as follows, Eq. (12).

$$z = \left[\vec{g}_s, \overleftarrow{g}_s\right] \tag{12}$$

The BiLSTM architecture processes traffic data in both directions, capturing temporal dependencies missed by unidirectional models. This allows it to incorporate both past trends and future context, leading to more accurate and stable traffic flow predictions in dynamic urban environments.

4.3. Malleable Aquila Optimization

MA Optimization is an advanced metaheuristic inspired by Aquila hunting strategies, with a self-modifying mechanism that improves its search methods based on changing optimization conditions. Traffic flow prediction in urban areas is challenged by dynamic conditions like weather, incidents, and varying traffic. The self-modifying MA optimizer adapts the DRN-BiLSTM model's hyperparameters in real-time, using mechanisms like SCF, GM, and ROBL to enhance performance and accuracy.

4.4. AO optimization

The AO approach can be enhanced by modeling Aquila's predator-prey activities using techniques like swooping, walking, and capturing prey, investigating within divergent and convergent search areas using contour flight, low flight with slow descent assault, and high soar with vertical stoop. An overview of these techniques is presented below.

4.5. Extended exploration (W_1)

The Aquila employs a vertical stoop and high soar to explore the solution region to identify the hunting region in this technique; the mathematical framework is described as Eq. (13) and.

$$W_1(s+1) = W_{\text{best}}(s) \times \left(1 - \frac{s}{s}\right) + \left(W_N(s) - W_{\text{bset}}(s).Q_1\right) \tag{13}$$

4.6. Constricted exploration (W_2)

In the subsequent technique, the Aquila flies in a spiral pattern above the target before executing an initial glide assault. The model calculation is explained as, Eq. (14).

$$W_2(s+1) = W_{\text{best}}(s) \times Ly(C) + W_Q(s) + (z-w).Q_2 \tag{14}$$

4.7. Extended exploitation (W_3)

The Aquila uses this technique to hunt by dropping vertically, searching the solution area by low flying, and then attacking the prey when the hunting region has been chosen.

The formula for the mathematical calculation is expressed as shown in Eq. (15),

$$W_3(s+1) = (W_{\text{best}}(s) - W_N(s))\,\alpha - Q_4 + [(UB - LB)\,Q_5 + LB]\,\delta \tag{15}$$

4.8. Constricted exploitation (W_4)

In the last approach, the Aquila attacks the target on the ground while following it in the absence of a random escape route.

4.9. Malleable Aquila (MA) Optimization Algorithm

Aquila search struggles in the solution area and often falls into local optima (LO) due to the LF operation in the second strategy of the standard AO approach. The third strategy limits local exploitation since the α value remains constant.

4.10. SCF

Consequently, when iterations (s) increase, the abs of SCF reduces, which is explained in Eq. (16),

$$\text{SCF}(s) = L_u \cdot \exp\left(1 - \frac{s}{s}\right) \times \text{Dir} \tag{16}$$

5. Result discussions

The MA-DRN-BiLSTM method was implemented in Python 3.11.5 on a Windows 11 laptop with an Intel i7 5th Gen processor and 16 GB of RAM. The approach was evaluated against traditional models such as LSTM-BiLSTM [27], GA-MENN [28], GRU [29], and W-CNNLSTM.

5.1. Correlation matrix

The relation between factors such as TF rate, moving speed, weather conditions, time of the day, and road physical characteristics is determined by the correlation matrix. This indicates how much each component is associated with TF and helps in formulating the models of predictions for enabling better assessment and control of traffic. The output of the correlation matrix is shown in Fig. 2.

R-squared (R^2) R^2 measures the percentage of variance in traffic flow (TF) explained by the model, with a value near 1 indicating strong predictive ability. Compared to traditional models like

LSTM-BiLSTM, GRU, and W-CNN-LSTM with R^2 values of 0.86, 0.91, and 0.94 , the MA-DRN-BiLSTM model achieves a higher R^2 of 0.97 , as shown in Fig. 3 and Table 1.

5.2. MAE

The MAE calculates the average relative difference between expected and observed traffic values. Compared to LSTM-BiLSTM, GA-MENN, and GRU with MAE values of 12.63, 11.25, and 26.72, the MA-DRN-BiLSTM approach achieves a lower MAE of 10.04, as shown in Fig. 4.

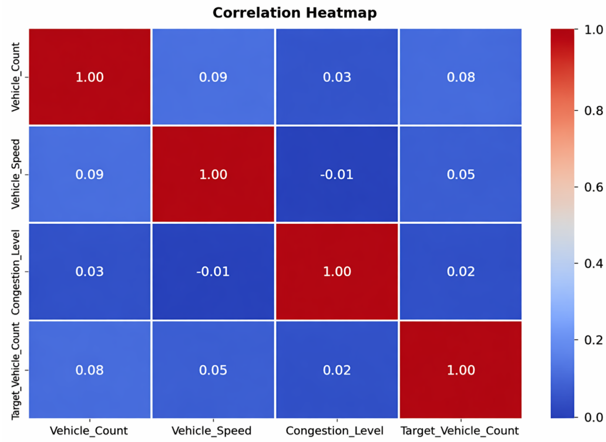

Fig. 2. Output of correlation matrix

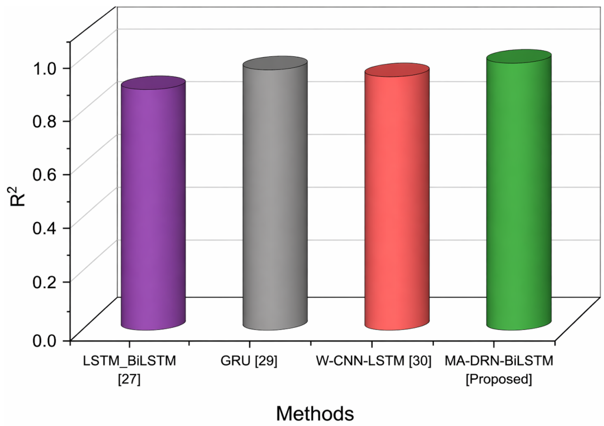

Fig. 3. Output of R^2 comparison

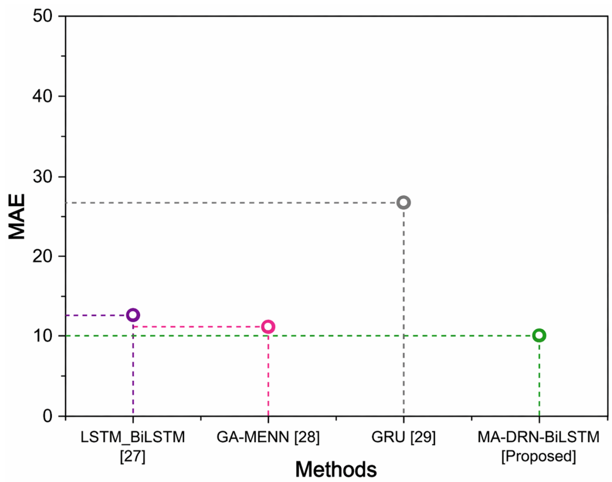

Fig. 4. Result of MAE

Table 1. Result of R^2 comparison

Methods	R^2
LSTM_BiLSTM	0.86
GRU	0.94
W-CNN-LSTM	0.91
MA-DRN-BiLSTM [Proposed]	0.97

Table 2. Result of MAE and RMSE

Methods	MAE	RMSE
LSTM_BiLSTM [27]	12.63	16.72
GA-MENN [28]	11.25	14.36
GRU [29]	26.72	41.33
MA-DRN-BiLSTM [Proposed]	10.04	12.14

5.3. RMSE

RMSE measures the squared differences between predicted and actual traffic density, making it key for evaluating traffic forecasting models. Compared to traditional models like LSTMBiLSTM, GA-MENN, and GRU with RMSE values of 16.72, 14.36, and 41.33 , the MA-DRN-BiLSTM model achieves a lower RMSE of 12.14, as shown in Fig. 5 and Table 2.

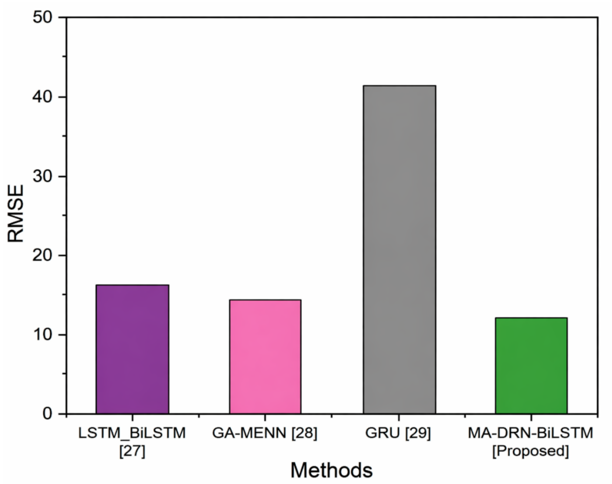

Fig. 5. Output of RMSE

The MA-DRN-BiLSTM model shows stable performance across varying traffic conditions, maintaining low RMSE and MAE during peak hours with high variability, and high R^2 during off-peak periods.

6. Discussion

Drawbacks of using LSTM_ BiLSTM [27] when estimating the TF of urban traffic include longer training times and increased computational problems caused by large amounts of Traffic information. The BiLSTM model outperforms LSTM by processing data in both directions, capturing both past and future traffic patterns. This bidirectional learning enhances traffic forecasting, especially in urban areas with rapidly changing conditions due to accidents or weather events. The BiLSTM layers, in combination with the Deep Recurrent Network (DRN) and Malleable Aquila Optimization (MA), capture long-term dependencies and adapt to real-time traffic conditions, improving prediction accuracy in dynamic environments. LSTM-based models and GA-MENN [28] struggle with overfitting and long-term dependencies in dynamic traffic environments. GRUs [29] underperform in complex systems, while W-CNN-LSTM are computationally intensive for real-time prediction.

7. Conclusion

Predicting urban traffic flow (TF) is crucial for improving transportation networks. This study introduces the MA-DRN-BiLSTM model, which effectively captures temporal and geographical relationships in traffic data. Evaluated with an R^2 of 0.97 , RMSE of 12.14, and MAE of 10.04, the model shows strong performance. However, it faces challenges with dynamic TF patterns, seasonal variations, and unusual traffic, affecting accuracy. Future improvements could focus on adaptive models, real-time data integration, and advanced anomaly detection to address these issues. The significance of the proposed MA-DRNBiLSTM model extends beyond predictive accuracy, as it provides practical support for intelligent urban traffic management under dynamic and unpredictable conditions. By effectively capturing nonlinear temporal dependencies and adapting to sudden traffic disruptions, the framework enables traffic authorities to implement proactive congestion control, optimize signal timing, and improve route planning strategies.

8. Declarations

9. Funding

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10. Conflicts of interests

Authors do not have any conflicts.

11. Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

12. Code availability

Not applicable.

13. Clinical trial number

Not applicable.

14. Consent to participate declaration, consent to publish declaration

Not applicable.

15. Ethics declaration

Not applicable.

16. Authors' contributions

Jinsheng Wang, Bo Liao, Fangxiang Wu, is responsible for designing the framework, analyzing the performance, validating the results, and writing the article.

Zhihao Jiang, Fei Tian is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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