UrbanFlow: Detailed Overview of All Models and Their Performance

UrbanFlow is a smart system designed to manage traffic lights to prioritize emergency vehicles and improve overall traffic flow. By predicting vehicle routes using various machine learning models, the system aims to enhance urban traffic management. Here's a detailed overview of all the models used in the project and their performance, with a focus on the best-performing ones.

Performance Metrics

- **MSE (Mean Squared Error):** Measures the average squared difference between predicted and actual values. Lower is better.
- **RMSE (Root Mean Squared Error):** The square root of MSE. Lower is better.
- **MAE (Mean Absolute Error):** The average absolute difference between predicted and actual values. Lower is better.
- **R^2 (Coefficient of Determination):** Indicates how well the model explains the variance in the target variable. Higher is better.
- **EVS (Explained Variance Score):** Measures the proportion of variance explained by the model. Higher is better.
- **MAPE (Mean Absolute Percentage Error):** The average absolute percentage difference between predicted and actual values. Lower is better.

Best Performing Models

1. Random Forest

Random Forest uses multiple decision trees to make predictions. Each tree gives a prediction, and the final result is a combination of all these predictions.

- **MSE:** 0.0009
- **RMSE:** 0.0307
- **MAE:** 0.004
- **R^2:** 0.999
- **EVS:** 0.999
- **MAPE:** 0.784%

Performance: Outstanding. This model makes almost perfect predictions.

2. XGBoost

XGBoost is an advanced model that builds multiple trees sequentially, each learning from the mistakes of the previous ones.

- **MSE:** 0.0057

- **RMSE:** 0.0753
- **MAE:** 0.024
- **R^2:** 0.994
- **EVS:** 0.994
- **MAPE:** 4.301%

Performance: Excellent. This model is highly accurate and reliable.

3. Ensemble Model

An ensemble model combines predictions from multiple models to improve accuracy. It's like getting opinions from various experts and combining them.

- **MSE:** 0.0040
- **RMSE:** 0.0635
- **MAE:** 0.029
- **R^2:** 0.996
- **EVS:** 0.996
- **MAPE:** 4.357%

Performance: Outstanding. This model leverages the strengths of multiple models for very high accuracy.

4. GRU (Gated Recurrent Unit)

GRU is a type of neural network that is particularly good at predicting sequences, like the future path of a vehicle.

- **MSE:** 0.0035
- **RMSE:** 0.0589
- **MAE:** 0.022
- **R^2:** 0.997
- **EVS:** 0.997
- **MAPE:** 5.063%

Performance: Outstanding. This model is very good at handling sequential data.

Other Models

5. CNN-LSTM

Combines Convolutional Neural Networks (CNN) and LSTMs. CNNs are great for spatial data, and LSTMs are good for time series data.

- **MSE:** 0.0115
- **RMSE:** 0.1075
- **MAE:** 0.052
- **R^2:** 0.988

- **EVS:** 0.988
- **MAPE:** 13.788%

Performance: Excellent. High accuracy and low error.

6. Stacked LSTM

Stacked LSTMs have multiple layers of LSTM units, enhancing their ability to capture complex patterns in the data.

- **MSE:** 0.9817
- **RMSE:** 0.9908
- **MAE:** 0.807
- **R^2:** 0.018
- **EVS:** 0.018
- **MAPE:** 100.345%

Performance: Slightly better than simple LSTM but still poor.

7. Optimized LSTM

An optimized version of LSTM aiming for better performance.

- **MSE:** 0.99999
- **RMSE:** 0.99999
- **MAE:** 0.815
- **R^2:** ~0
- **EVS:** ~0
- **MAPE:** 99.997%

Performance: Very poor, nearly no predictive power.

8. BiLSTM

Bidirectional LSTM processes data in both forward and backward directions.

- **MSE:** 0.99997
- **RMSE:** 0.99998
- **MAE:** 0.815
- **R^2:** ~0.00003
- **EVS:** ~0.00003
- **MAPE:** 99.909%

Performance: Very poor, similar to Optimized LSTM.

9. SVM (Support Vector Machine)

SVM finds the best boundary that separates different classes of data.

- **MSE:** 0.0594
- **RMSE:** 0.2436
- **MAE:** 0.089
- **R^2:** 0.941
- **EVS:** 0.941
- **MAPE:** 24.444%

Performance: Good, relatively high accuracy.

10. k-NN (k-Nearest Neighbors)

k-NN predicts the output based on the closest data points.

- **MSE:** 0.0505
- **RMSE:** 0.2247
- **MAE:** 0.139
- **R^2:** 0.949
- **EVS:** 0.950
- **MAPE:** 44.521%

Performance: Decent, moderate accuracy.

11. Regularized Stacking

Combines multiple models with regularization to prevent overfitting.

- **MSE:** 0.0113
- **RMSE:** 0.1065
- **MAE:** 0.049
- **R^2:** 0.989
- **EVS:** 0.989
- **MAPE:** 12.998%

Performance: Excellent, very high accuracy.

12. Weighted Average

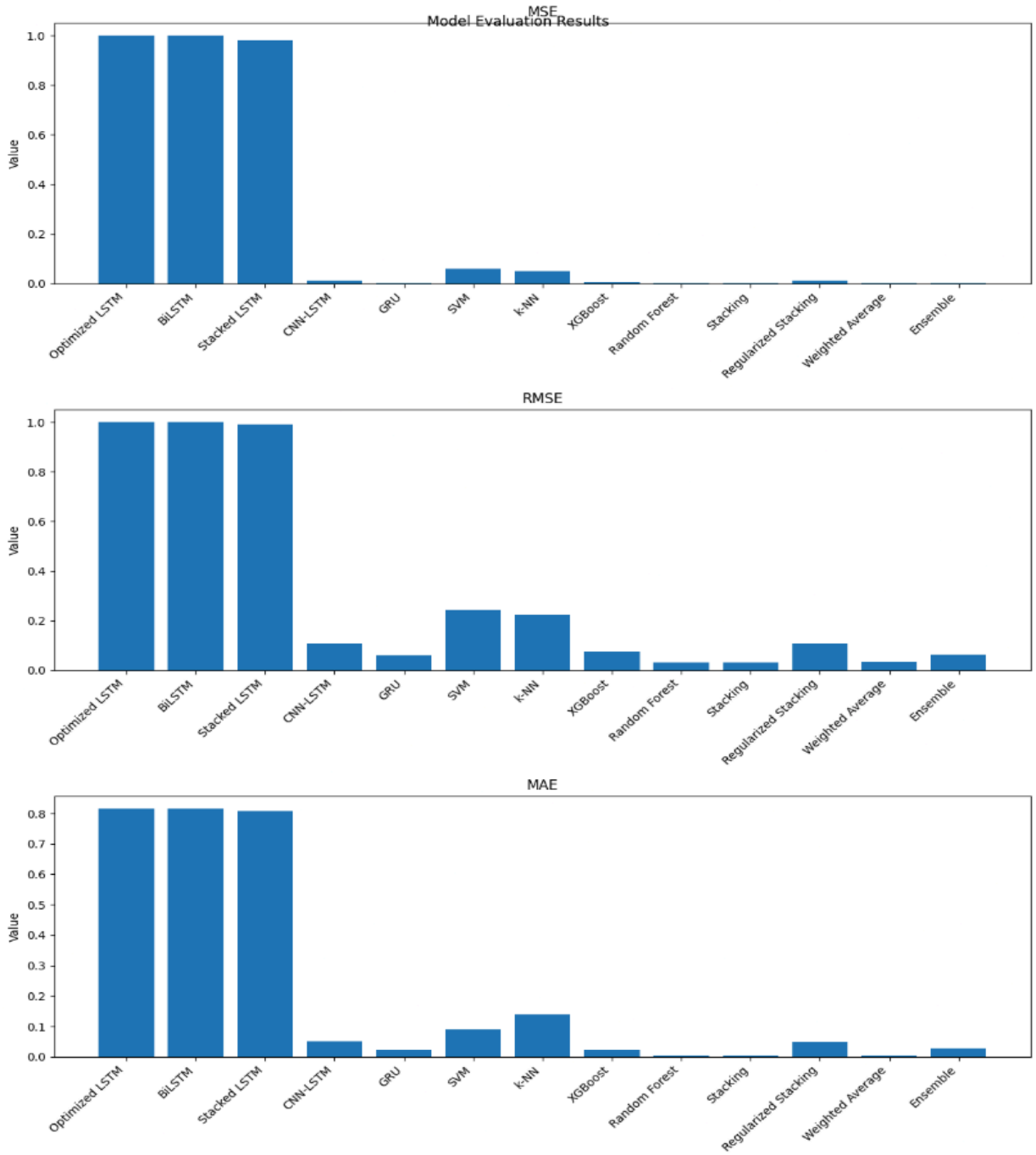
Combines predictions of different models, giving different weights to each model.

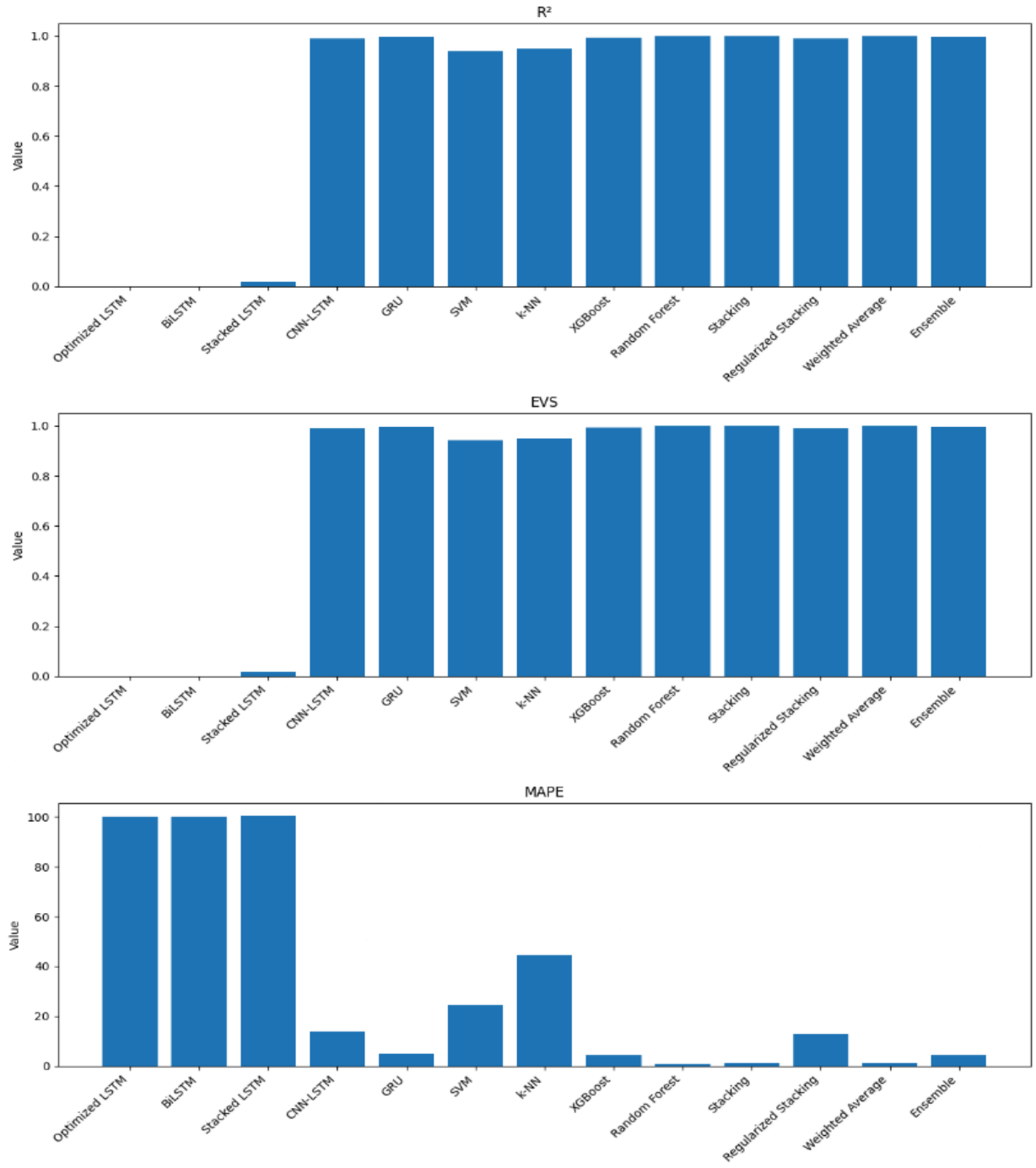
- **MSE:** 0.0011
- **RMSE:** 0.0327
- **MAE:** 0.005
- **R^2:** 0.999
- **EVS:** 0.999
- **MAPE:** 1.107%

Performance: Excellent, very high accuracy.

Performance Summary Chart

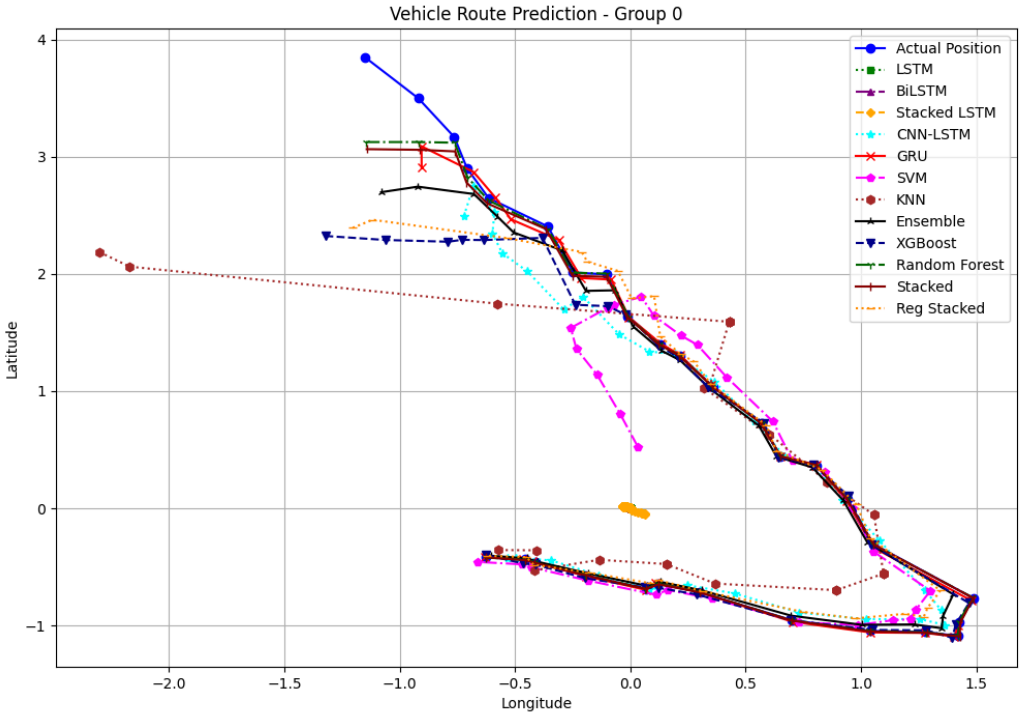
Model	MSE	RMSE	MAE	R^2	EVS	MAPE	Performance
Random Forest	0.0009	0.0307	0.004	0.999	0.999	0.784%	Outstanding
XGBoost	0.0057	0.0753	0.024	0.994	0.994	4.301%	Excellent
Ensemble	0.0040	0.0635	0.029	0.996	0.996	4.357%	Outstanding
GRU	0.0035	0.0589	0.022	0.997	0.997	5.063%	Outstanding
CNN-LSTM	0.0115	0.1075	0.052	0.988	0.988	13.788%	Excellent
Stacked LSTM	0.9817	0.9908	0.807	0.018	0.018	100.345%	Poor
Optimized LSTM	0.99999	0.99999	0.815	~0	~0	99.997%	Very Poor
BiLSTM	0.99997	0.99998	0.815	~0.00003	~0.00003	99.909%	Very Poor
SVM	0.0594	0.2436	0.089	0.941	0.941	24.444%	Good
k-NN	0.0505	0.2247	0.139	0.949	0.950	44.521%	Decent
Regularized Stacking	0.0113	0.1065	0.049	0.989	0.989	12.998%	Excellent
Weighted Average	0.0011	0.0327	0.005	0.999	0.999	1.107%	Excellent

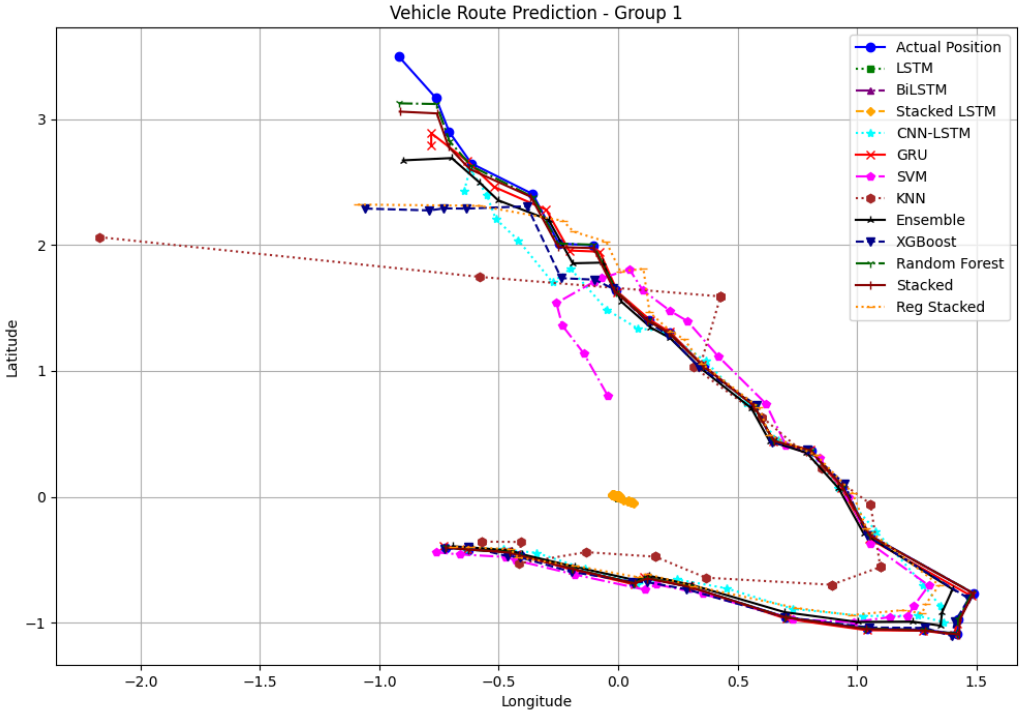

MSE
Model Evaluation Results
Value
0.0
0.2
0.4
0.6
0.8
1.0
Optimized LSTM
BiLSTM
Stacked LSTM
CNN-LSTM
GRU
SVM
k-NN
XGBoost
Random Forest
Stacking
Regularized Stacking
Weighted Average
Ensemble
RMSE
Value
0.0
0.2
0.4
0.6
0.8
1.0
Optimized LSTM
BiLSTM
Stacked LSTM
CNN-LSTM
GRU
SVM
k-NN
XGBoost
Random Forest
Stacking
Regularized Stacking
Weighted Average
Ensemble
MAE
Value
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Optimized LSTM
BiLSTM
Stacked LSTM
CNN-LSTM
GRU
SVM
k-NN
XGBoost
Random Forest
Stacking
Regularized Stacking
Weighted Average
Ensemble

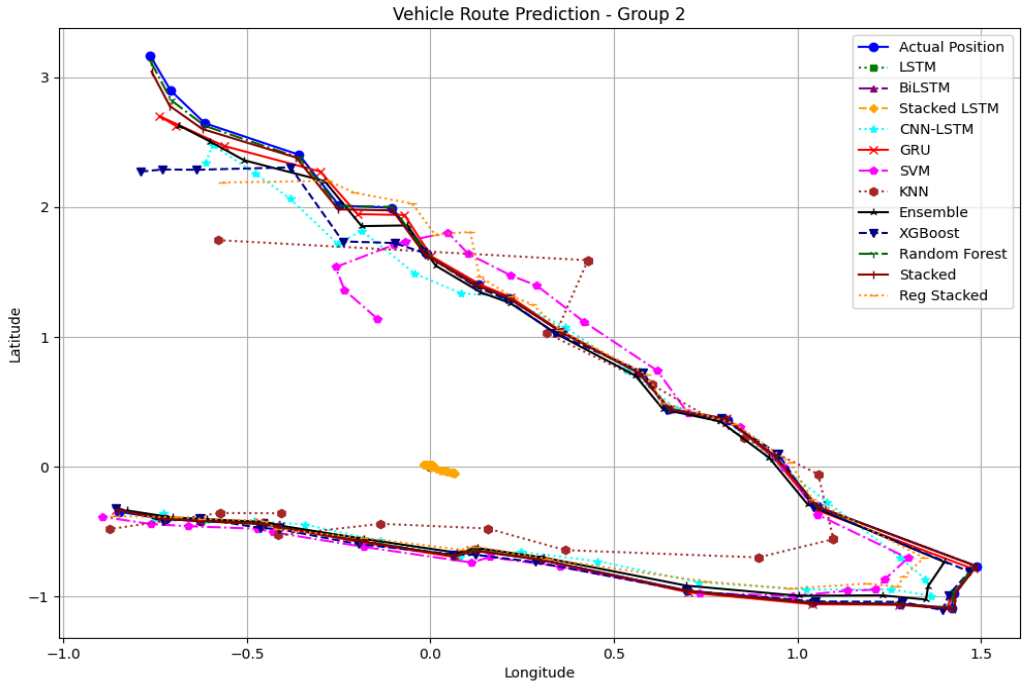


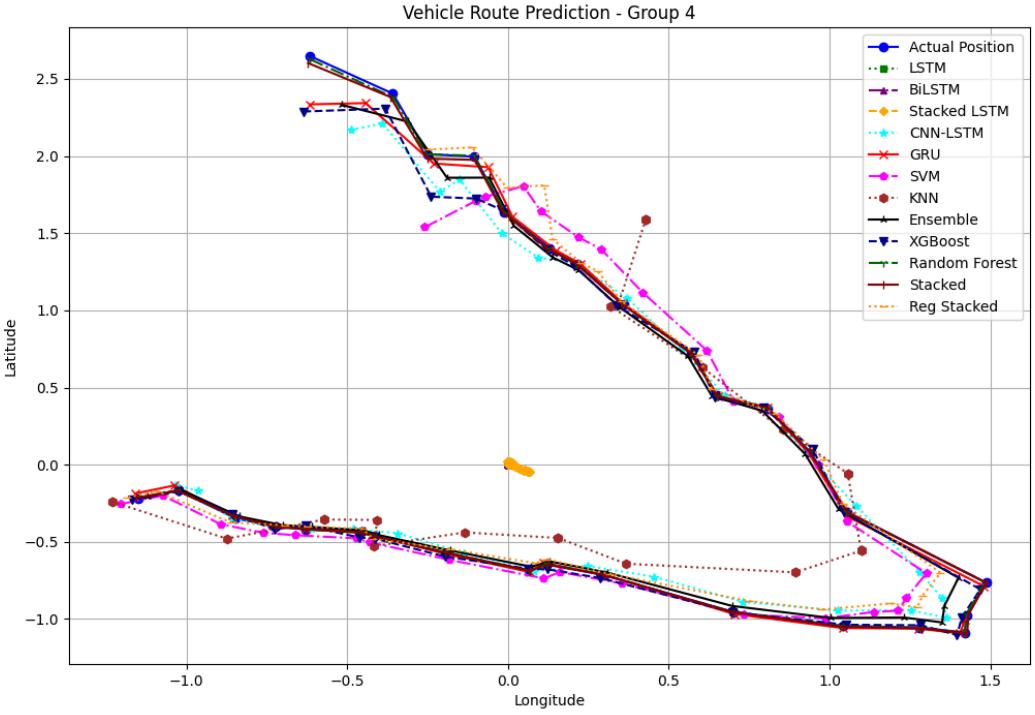
Visual Analysis of Predictions

The visual predictions demonstrate a strong alignment with the actual paths across all models, showcasing their effectiveness in capturing the underlying trends.


Vehicle Route Prediction - Group 0
Actual Position
LSTM
BiLSTM
Stacked LSTM
CNN-LSTM
GRU
SVM
KNN
Ensemble
XGBoost
Random Forest
Stacked
Reg Stacked
Latitude
Longitude
4
3
2
1
0
−1
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Vehicle Route Prediction - Group 1
Actual Position
LSTM
BiLSTM
Stacked LSTM
CNN-LSTM
GRU
SVM
KNN
Ensemble
XGBoost
Random Forest
Stacked
Reg Stacked
Latitude
Longitude
3
2
1
0
−1
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5





Random Forest

- Closely follows the actual path, indicating high reliability and accurate predictions.
- Displays the best visual alignment among all models, suggesting superior predictive capability.

- Provides accurate predictions, closely following the actual path consistently.

XGBoost

- Exhibits minor deviations but remains very close to the actual path, confirming its robustness.
- Maintains a very close alignment, further validating its effectiveness.
- Shows high accuracy with only minor deviations across all datasets.

Ensemble

- Aligns closely with the actual path, reinforcing the accuracy of the ensemble approach.
- Achieves excellent alignment, validating the ensemble method's effectiveness.
- Demonstrates very close alignment with the actual path, echoing the performance of other models.

Conclusion

The UrbanFlow project shows how different machine learning models can be used to predict vehicle routes and improve traffic management. The best-performing models, such as Random Forest, XGBoost, Ensemble, and GRU, offer high accuracy and reliability, making them ideal for optimizing urban traffic flow. Other models, while not as accurate, provide insights into different approaches to solving the problem.