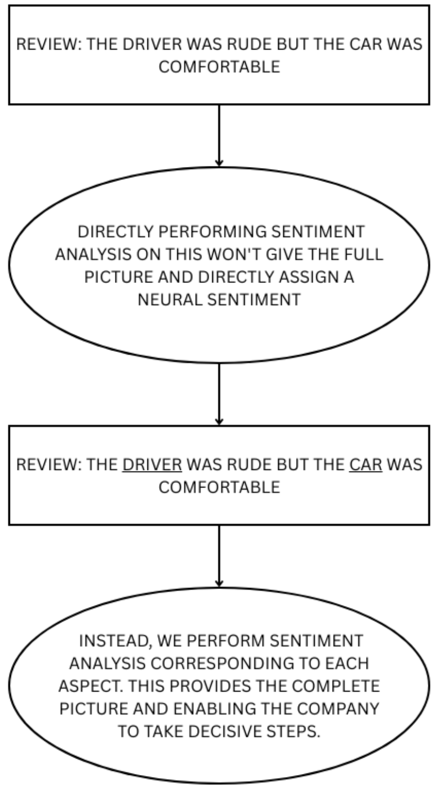
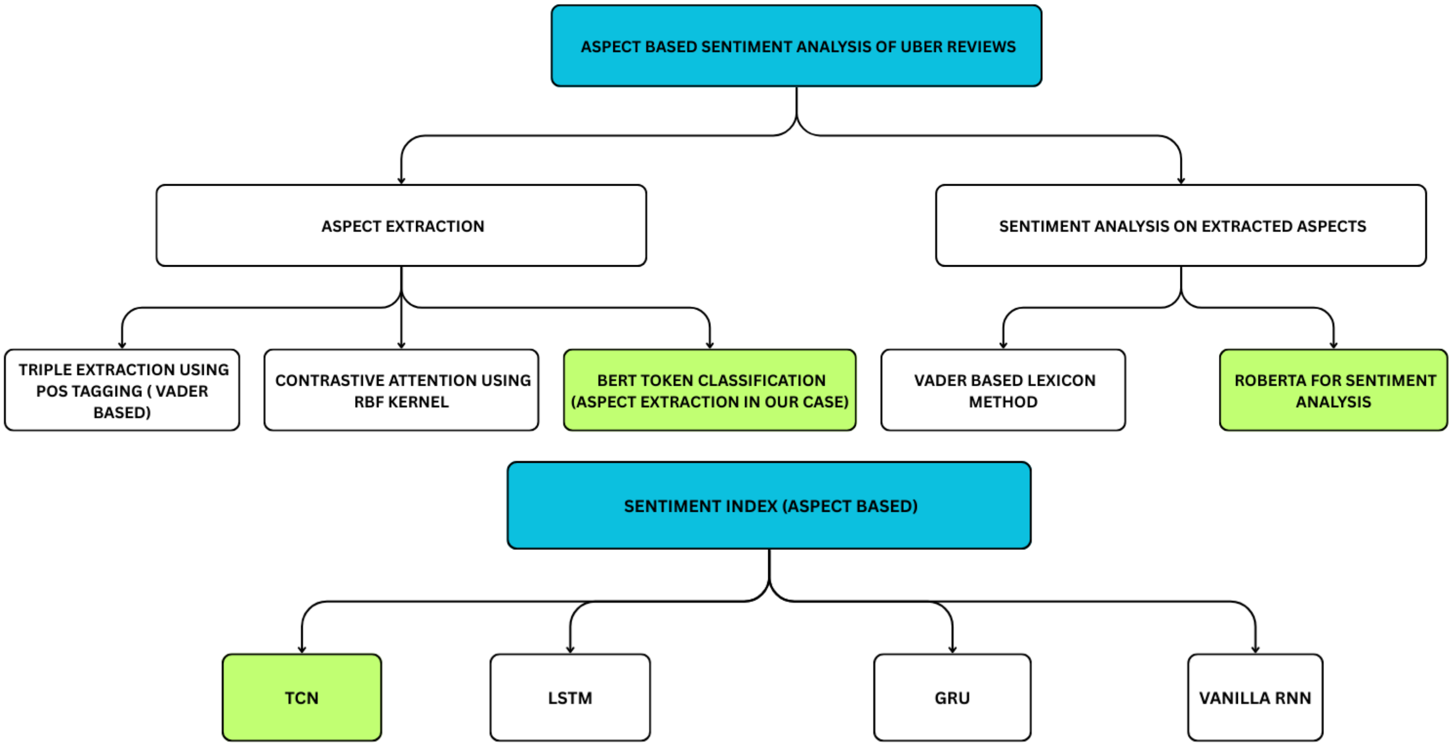
Aspect-Based Sentiment Index Forecasting Using Deep Learning Networks on Uber Reviews

PROBLEM STATEMENT

- Most sentiment analysis systems provide only an overall polarity of user feedback, which obscures the specific areas driving customer satisfaction or dissatisfaction. This limits a company's ability to take focused, data-driven action. This project addresses that gap by applying **Aspect-Based Sentiment Analysis (ABSA)** to Uber reviews, enabling the extraction of sentiments tied to individual service components like drivers, app performance, and pricing. By combining ABSA with time-series forecasting, the project empowers Uber to track sentiment trends over time and make targeted improvements where it matters most.

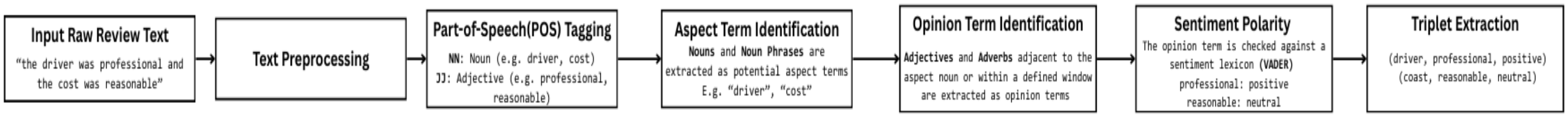

REVIEW: THE DRIVER WAS RUDE BUT THE CAR WAS COMFORTABLE
DIRECTLY PERFORMING SENTIMENT ANALYSIS ON THIS WON'T GIVE THE FULL PICTURE AND DIRECTLY ASSIGN A NEURAL SENTIMENT
REVIEW: THE DRIVER WAS RUDE BUT THE CAR WAS COMFORTABLE
INSTEAD, WE PERFORM SENTIMENT ANALYSIS CORRESPONDING TO EACH ASPECT. THIS PROVIDES THE COMPLETE PICTURE AND ENABLING THE COMPANY TO TAKE DECISIVE STEPS.

END TO END SOLUTION PIPELINE

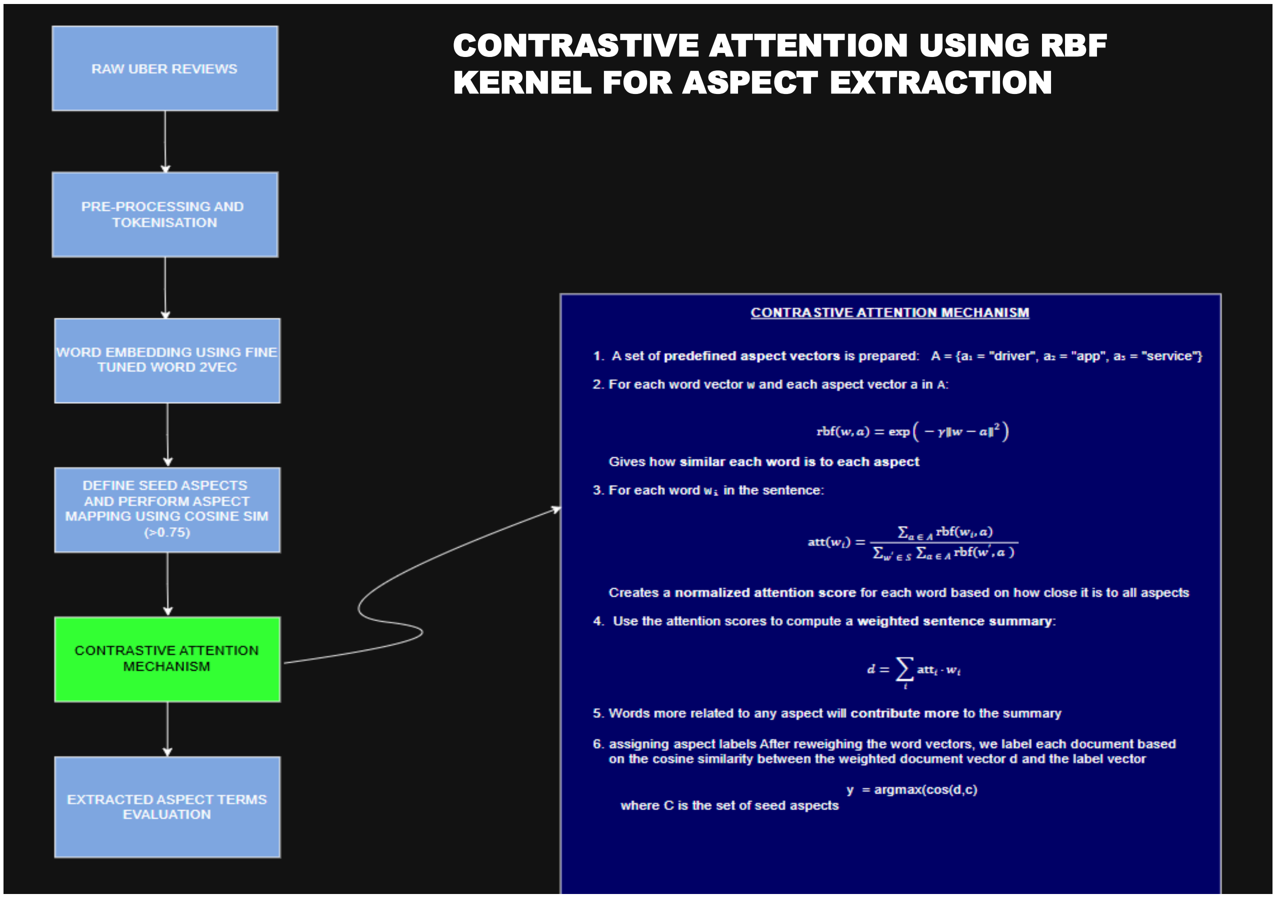


ASPECT EXTRACTION METHOD 1:
TRIPLET EXTRACTION – (WHAT, HOW AND WHY)USING POS-TAGGING

WHAT :ASPECT
HOW : SENTIMENT
WHY :OPINION

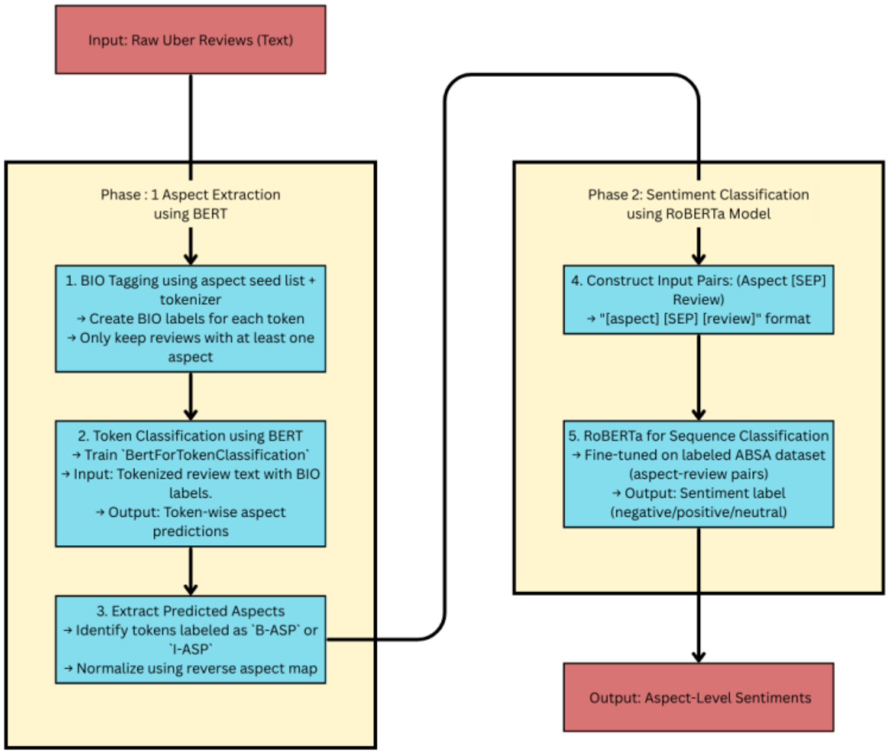


	review	aspect	sentiment	opinion
0	Michelle was a very friendly and personable pe...	driver	positive	friendly
1	Bast price pr car available	fare	neutral	available
2	Bast price pr car available	pr	neutral	available
3	Bast price pr car available	car	neutral	available
4	Good service	service	positive	good
...	...	...	...	...
13888	Very bad experience with this app, booked a sh...	experience	negative	bad



CONTRASTIVE ATTENTION USING RBF KERNEL FOR ASPECT EXTRACTION
RAW UBER REVIEWS
PRE-PROCESSING AND TOKENISATION
WORD EMBEDDING USING FINE TUNED WORD 2VEC
DEFINE SEED ASPECTS AND PERFORM ASPECT MAPPING USING COSINE SIM (>0.75)
CONTRASTIVE ATTENTION MECHANISM
EXTRACTED ASPECT TERMS EVALUATION
CONTRASTIVE ATTENTION MECHANISM
1. A set of predefined aspect vectors is prepared: A = {a_1 = "driver", a_2 = "app", a_3 = "service"}
2. For each word vector w and each aspect vector a in A:
$\mathrm{rbf}(w, a) = \exp\left(-\gamma \|w - a\|^2\right)$
Gives how similar each word is to each aspect
3. For each word w_i in the sentence:
$\mathrm{att}(w_i) = \frac{\sum_{a \in A} \mathrm{rbf}(w_i, a)}{\sum_{w' \in S} \sum_{a \in A} \mathrm{rbf}(w', a)}$
Creates a normalized attention score for each word based on how close it is to all aspects
4. Use the attention scores to compute a weighted sentence summary:
$d = \sum_i \mathrm{att}_i \cdot w_i$
5. Words more related to any aspect will contribute more to the summary
6. assigning aspect labels After reweighing the word vectors, we label each document based on the cosine similarity between the weighted document vector d and the label vector
y = argmax(cos(d,c))
where C is the set of seed aspects

BERT BASED ASPECT EXTRACTION (TOKEN CLASSIFICATION) AND SENTIMENT ANALYSIS USING ROBERTA

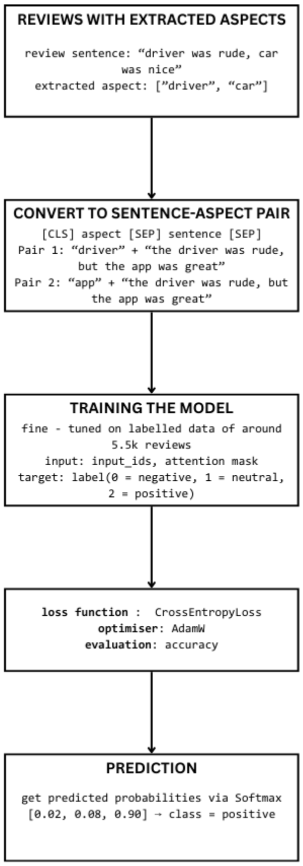


ASPECT EXTRACTION EVALUATION AND COMPARISION

A manually created GOLD STANDARD DATASET (reviews with their manually extracted aspects) was creating to evaluate each model on. BERT performed the best and was the chosen model for aspect based sentiment analysis

1	review	aspect
2	Efficient, driver is professional, cost is reasonable	driver
3	Efficient, driver is professional, cost is reasonable	fare
4	Waiting charge is extra bad experience	wait
5	Good service	service
6	Worst customer service On 19/11/24 I booked an auto the driver cancelled and I was asked to pas t	driver
7	Worst customer service On 19/11/24 I booked an auto the driver cancelled and I was asked to pas t	app
8	Worst customer service On 19/11/24 I booked an auto the driver cancelled and I was asked to pas t	service
9	Reliable and timescale and easy tovl use with good prices	fare
10	Cool, respectful drivers	driver
11	Always a pleasure to ride with Uber drivers. Quick pick ups all the time	driver
12	Good service...	service
13	Quick service on a busy Friday evening.	service
14	It is a cheating app. While booking the ride it shows as 400 rupees and it increases to 680 while dro	driver
15	It is a cheating app. While booking the ride it shows as 400 rupees and it increases to 680 while dro	fare
16	It is a cheating app. While booking the ride it shows as 400 rupees and it increases to 680 while dro	app
17	Love the app and convenient application	app
18	I love that app	app

Model	POS Tagging	BERT	CAT
Precision	0.366	0.757	0.791
Recall	0.486	0.875	0.422
F1 Score	0.417	0.812	0.532

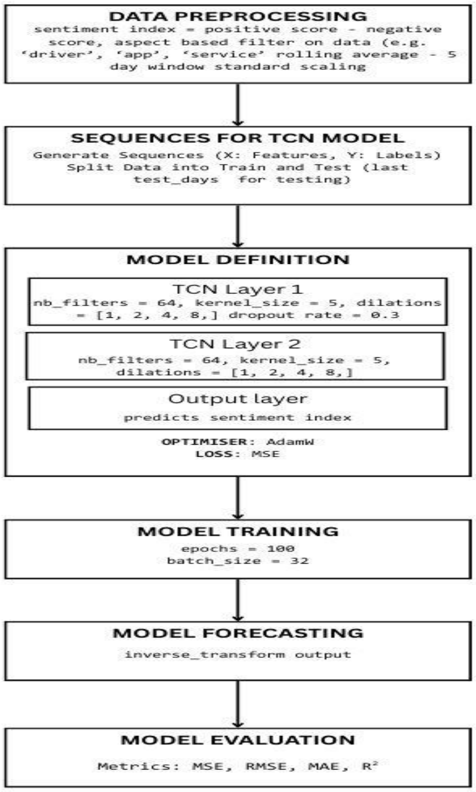


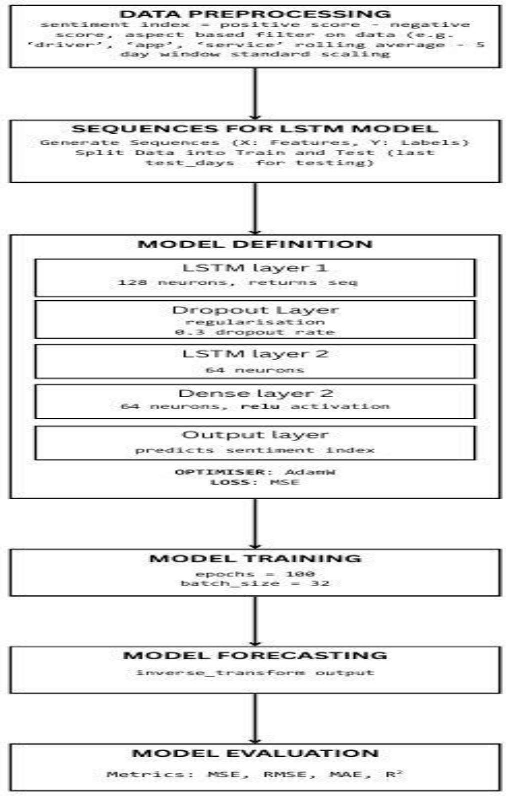
ROBERTA FOR SENTIMENT ANALYSIS ON EXTRACTED ASPECTS USING BERT

DATASET AFTER PERFORMING ABSA WITH SENTIMENT SCORES AND LABELS CORRESPONDING TO ASPECT AND REVIEW:

Today one horrible experience I faced ...I booked one Uber go for on	18-12-2024 16:32	uber	0.999224305	0.000321	0.000455	negative
Today one horrible experience I faced ...I booked one Uber go for on	18-12-2024 16:32	drop	0.999217272	0.000325	0.000458	negative
Quick and reliable.	18-12-2024 16:29	uber	0.000300214	0.999411	0.000289	positive
Super rides with reasonable amount	18-12-2024 16:26	amount	0.000595407	0.00041	0.998995	neutral
Amazing application	18-12-2024 16:25	application	0.000225974	0.999509	0.000265	positive
Supre app	18-12-2024 16:24	app	0.000585184	0.000476	0.998939	neutral
Good	18-12-2024 16:19	uber	0.00023826	0.999529	0.000233	positive
The safest way to travel.	18-12-2024 16:15	travel.	0.004753225	0.431536	0.563711	neutral
Amazing	18-12-2024 16:13	uber	0.000214094	0.999513	0.000273	positive
Prompt and Cool	18-12-2024 16:13	uber	0.000243924	0.989812	0.009944	positive
Horrible, bunch of thieves. The fare you see when booking versus the	18-12-2024 16:09	trip	0.00049248	0.000616	0.998892	neutral
Horrible, bunch of thieves. The fare you see when booking versus the	18-12-2024 16:09	fare	0.000488458	0.000626	0.998886	neutral
Horrible, bunch of thieves. The fare you see when booking versus the	18-12-2024 16:09	uber.	0.000520652	0.000587	0.998893	neutral
Horrible, bunch of thieves. The fare you see when booking versus the	18-12-2024 16:09	booking	0.000513161	0.000553	0.998934	neutral
Superb	18-12-2024 16:08	uber	0.000552034	0.000404	0.999044	neutral
Good service	18-12-2024 16:07	service	0.000226962	0.99953	0.000243	positive
Very helpful	18-12-2024 15:56	uber	0.000241697	0.999448	0.00031	positive

Aspect Based Sentiment Forecasting Model





Evaluation Metrics Used

1. Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

2. Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

3. Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

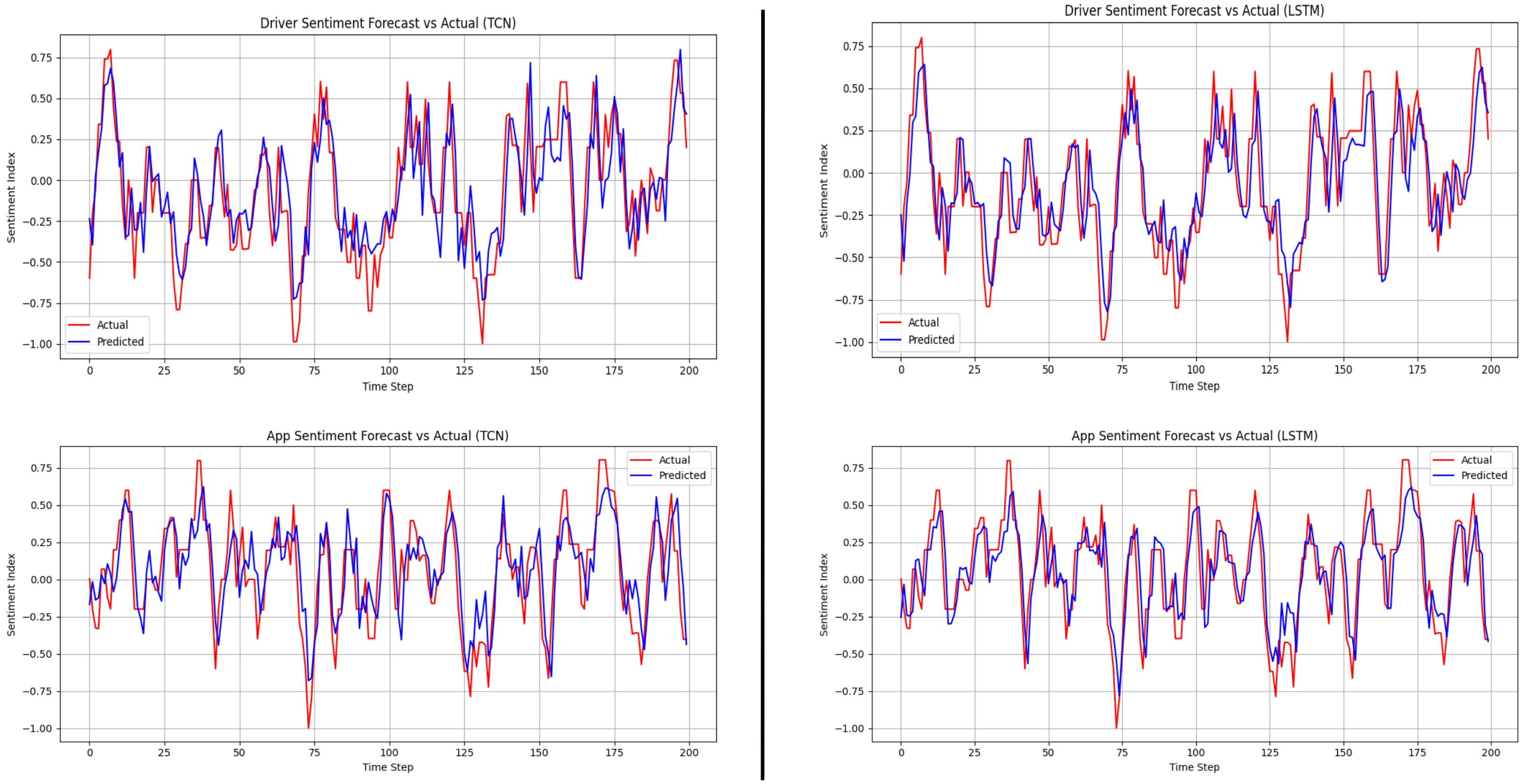
4. $\mathbf{R^2}$ Score (Coefficient of Determination)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Model Result with 3 different Baseline Models

Model	Metric	Driver	Uber	Service	App
TCN	MSE	0.0469	0.0285	0.0296	0.0446
	RMSE	0.2167	0.1691	0.1722	0.2113
	MAE	0.1827	0.1359	0.1335	0.1761
	R^2	0.6833	0.5157	0.7576	0.6332
LSTM	MSE	0.0513	0.0273	0.0348	0.0438
	RMSE	0.2265	0.1653	0.1864	0.2093
	MAE	0.1848	0.1310	0.1469	0.1688
	R^2	0.6545	0.5372	0.7159	0.6403
GRU	MSE	0.0515	0.0270	0.0325	0.0444
	RMSE	0.2269	0.1643	0.1803	0.2107
	MAE	0.1855	0.1306	0.1426	0.1716
	R^2	0.6530	0.5428	0.7344	0.6355
RNN	MSE	0.0525	0.0269	0.0338	0.0447
	RMSE	0.2291	0.1641	0.1837	0.2114
	MAE	0.1878	0.1311	0.1454	0.1767
	R^2	0.6464	0.5442	0.7240	0.6332

Actual Vs Predicted Plots of our Model and Baseline Model



Thank You