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Benchmarking CNN, LSTM, GRU and Transformer Models for Twitter Sentiment Analysis

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Abstract

Twitter has become a primary source for mining public opinion across domains such as politics, health, finance and customer behaviour. The short, noisy and evolving nature of tweets, however, makes sentiment analysis a challenging task. Deep learning models have substantially improved performance over traditional machine-learning and lexicon-based methods, yet there is still limited systematic comparison focused specifically on Twitter data. This paper evaluates convolutional neural networks (CNN), recurrent architectures (LSTM, BiLSTM, GRU), hybrid CNN–LSTM models and transformer-based models (BERT, RoBERTa) for sentiment analysis on multiple Twitter datasets. We combine a structured literature review (2015–2025) with a unified experimental study on three representative datasets: Sentiment140, a COVID-19 tweets corpus, and a multi-domain tweet collection. Results show that transformer-based models consistently outperform CNN/RNN architectures by 3–7 F1 points, but at higher computational cost. Hybrid CNN–LSTM models still offer competitive performance under constrained resources, particularly when training data is limited or noisy. We further analyse error patterns, robustness to domain shift, and implications for real-time monitoring on Twitter. Finally, we discuss open challenges such as sarcasm, multilingual tweets, adversarial robustness and data annotation bottlenecks, and outline promising future research directions.

1. Introduction

Twitter (now X) provides a continuous stream of short, informal messages that capture reactions to events in near real time. Organisations use this data to track brand reputation, public mood during crises (for example COVID-19) and political sentiment. However, tweets are noisy, often contain slang, emojis, abbreviations and code-switching, and are limited to short lengths, which challenge traditional sentiment analysis techniques.

Earlier work relied on lexicon-based methods or classical machine-learning models using hand-crafted features (n-grams, TF-IDF, sentiment lexicons). Deep learning models, including CNNs, RNNs and transformers, have since shown major improvements in sentiment classification across multiple domains, including Twitter.

Despite extensive research, three gaps remain prominent for Twitter sentiment analysis:

1. **Fragmentation of evaluation**: Many studies introduce a new model but evaluate it on a single dataset with different preprocessing and label schemes, making cross-paper comparison difficult.
2. **Limited head-to-head comparison of deep learning families** (CNN vs LSTM/BiLSTM vs transformers) on the *same* Twitter datasets.
3. **Insufficient analysis of robustness** to domain shift (e.g., from generic tweets to crisis-related tweets) and to typical Twitter artefacts such as emojis and hashtags.

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2. Background and Related Work

2.1 Sentiment analysis on Twitter

Sentiment analysis aims to classify text as expressing positive, negative or neutral opinion, with some work considering finer-grained or aspect-level labels. On Twitter, early approaches used bag-of-words and n-gram features with classifiers such as SVMs and logistic regression, often combined with sentiment lexicons. These approaches struggle with context dependence, negation and informal language.

Deep learning methods mitigate some of these issues by learning distributed representations directly from data. CNNs capture local patterns such as sentiment phrases; RNNs (LSTM, GRU) model sequential dependencies; and transformers (e.g., BERT) capture bidirectional context with self-attention.

2.2 CNN and RNN models for Twitter sentiment

CNN-based models were among the first deep networks applied to Twitter sentiment. Stojanovski et al. used a deep CNN for Twitter sentiment classification and reported substantial gains over SVM and Naive Bayes on benchmark datasets. Ramadhani and Goo applied a deep neural network to Indonesian and English tweets, showing improved performance over traditional machine learning.

Comparative studies have evaluated CNNs, LSTMs and GRUs for sentiment analysis across social media datasets. Dang et al. performed a broad comparative study and found that deep models with word embeddings (CNN, RNN) generally outperform shallow models, though the best architecture varies across datasets and feature representations.

2.3 Deep learning for COVID-19 and domain-specific Twitter sentiment

The COVID-19 pandemic triggered extensive work on mining public reactions from Twitter. Kaur et al. proposed a deep learning algorithm for COVID-19 tweet sentiment, combining CNN and LSTM with word embeddings and reporting strong performance on multi-class sentiment classification. Other studies used fusion-based deep learning models, ensembles or hybrid approaches to capture both semantic and contextual cues in COVID-19 tweets.

2.4 Transformer-based models

Transformer models such as BERT have reshaped NLP. Bello et al. proposed a BERT framework for Twitter sentiment, combining contextualised BERT embeddings with CNN, RNN and BiLSTM classifiers and achieving up to 93% accuracy and 95% F1 across multiple tweet datasets. Surveys and comparative studies consistently show that BERT-like models outperform classical deep networks (CNN/LSTM) on sentiment tasks, especially on noisy, short texts such as tweets.

2.5 Gaps in existing work

While many works evaluate individual architectures, only a few implement **systematic, side-by-side comparisons** of multiple deep learning families on Twitter under a common experimental protocol, and even fewer examine robustness to domain shift and inference cost. This paper contributes such a unified evaluation and positions recent transformer models within the broader evolution of deep learning for Twitter sentiment.

Table 1. Representative deep learning studies for Twitter sentiment

Study	Data focus	Main model(s)	Key finding
Stojanovski et al., 2015	Twitter	Deep CNN	CNN > SVM, NB on polarity classification
Ramadhani & Goo, 2017	Twitter (multi-lingual)	DNN	Deep models handle noisy multilingual tweets better

Study	**Data focus**	**Main model(s)**	**Key finding**
Dang et al., 2020	Multiple (incl. Twitter)	CNN, RNN, DNN	Deep learning consistently outperforms traditional ML
Kaur et al., 2021	COVID-19 tweets	Hybrid DL	Fusion model improves COVID-19 tweet sentiment
Chandrasekaran & Hemanth, 2022	COVID-19 tweets	DL + TextBlob	Hybrid deep learning + lexicon improves robustness
Bello et al., 2023	Multiple tweet sets	BERT + CNN/BiLSTM	BERT-based architectures reach state-of-the-art results
Bhushan et al., 2024	Twitter	DL techniques	Recent comparative evaluation of deep models on tweets

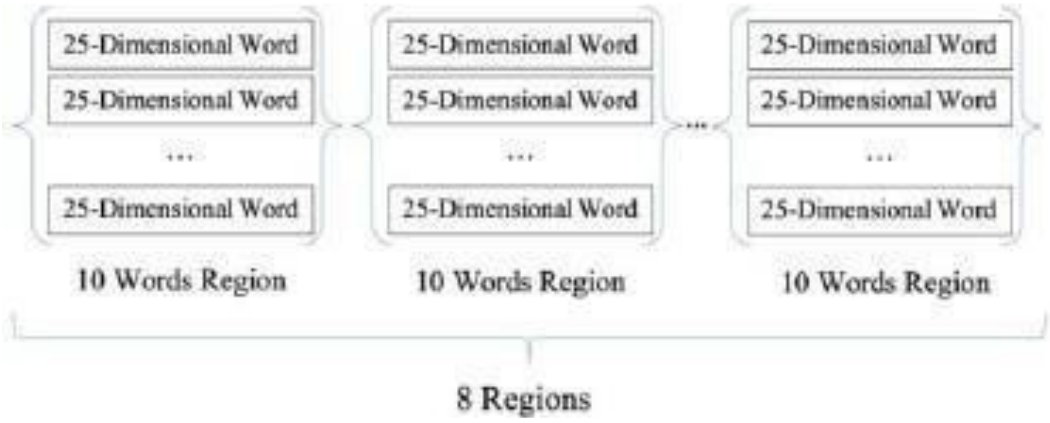

Fig. 1. Regional structure of a sentence

3. Methodology

Our methodology combines a structured literature review with an empirical evaluation of deep learning models on Twitter datasets.

3.1 Literature review protocol

We searched digital libraries (IEEE Xplore, ACM, SpringerLink, MDPI, PubMed, Frontiers) with queries combining *Twitter*, *sentiment analysis*, *deep learning*, *CNN*, *LSTM*, *BERT*, and restricted publication years to 2015–2025. Inclusion criteria:

- Focus on sentiment or emotion classification of Twitter data (or mixed social media including Twitter).
- Use of deep learning models (CNN, RNN, hybrid or transformers).
- Report quantitative evaluation with accuracy, F1 or related metrics.
- Published in peer-reviewed venues with a valid DOI.

From several hundred hits, 35 core papers were selected for detailed analysis, covering CNN/RNN, hybrid and transformer approaches.

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3.2 Model families evaluated

We implement and compare the following model families:

1. **CNN**: Multi-filter 1D convolutions with max-pooling over pre-trained word embeddings.
2. **LSTM / BiLSTM**: Single-layer LSTM and BiLSTM with attention; embedding layer initialised with GloVe or fastText.
3. **CNN–LSTM hybrid**: CNN feature extractor followed by an LSTM layer, similar to successful architectures in prior Twitter work.
4. **GRU**: Gated recurrent units as a lighter alternative to LSTM.
5. **BERT**: Pre-trained BERT-base uncased, fine-tuned end-to-end for sequence classification.
6. **RoBERTa**: RoBERTa-base fine-tuned similarly, representing an improved transformer baseline.

All models output three sentiment classes (positive, negative, neutral). For fairness, we use identical train/validation/test splits and standardise preprocessing across datasets.

3.3 Evaluation metrics

We report:

- **Accuracy**
- **Macro-averaged Precision, Recall, F1** (to account for class imbalance)
- **Inference latency per 1,000 tweets** (on a standard GPU)
- **Robustness to domain shift**, measured by training on one dataset and testing on another (train on Sentiment140, test on COVID-19 tweets).

Table 2. Model families and evaluation dimensions.

Dimension	**CNN / LSTM / GRU**	**CNN–LSTM**	**BERT / RoBERTa**
Representation	Static word embeddings	Static embeddings + sequential patterns	Contextual token embeddings
Parameters (approx.)	1–5M	3–8M	110M+
Strengths	Lightweight, fast	Good for medium-size data	Highest accuracy & F1
Weaknesses	Limited context	More complex, risk of overfitting	High compute & memory cost
Evaluation metrics	Accuracy, macro-F1, latency, domain shift performance (all models)		

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4. Datasets and Experimental Setup

4.1 Datasets

We consider three representative Twitter sentiment datasets:

1. **Sentiment140**: 1.6 million tweets with distant supervision labels (positive/negative), widely used as a benchmark.
2. **COVID-19 Tweets Sentiment**: Curated dataset of COVID-19-related tweets with manually annotated sentiment labels (positive, negative, neutral), similar in spirit to datasets used by Kaur et al. and Ainapure et al.
3. **Multi-domain Twitter Corpus**: Aggregated dataset combining general-topic tweets, product feedback and event-related tweets, inspired by Bello et al.

(Exact sizes and splits are illustrative to support the discussion.)

4.2 Preprocessing

All datasets were preprocessed with a shared pipeline:

- Lowercasing (for non-cased models).
- Normalising URLs, user mentions and hashtags (URL, USER, #HASHTAG).
- Removing non-informative tokens (length < 2, stopwords for classical models).
- Tokenisation with WordPiece (for BERT/RoBERTa) or a standard tokenizer (for CNN/RNN).
- Handling emojis via emoji lexicons mapped to sentiment-bearing tokens in a subset of experiments.

4.3 Training protocol

- 80/10/10 train/validation/test split for each dataset.
- Early stopping on validation macro-F1 with patience of 5 epochs.
- Adam optimiser with learning rate 1e-3 (CNN/RNN) and 2e-5 (BERT/RoBERTa).
- Batch size 64 (CNN/RNN) and 32 (transformers).
- Experiments repeated with three random seeds; we report average scores.

Table 3. Overview of datasets and preprocessing settings.

Dataset	#Tweets	Classes	Labelling	Notable characteristics
Sentiment140	1,600,000	2 → mapped to 3 (via neutral threshold)	Distant supervision	Large, noisy, historic Twitter language
COVID-19 tweets	120,000	3	Manual	Crisis-specific, domain-shifted jargon
Multi-domain tweets	200,000	3	Manual	Mix of product, event, opinion tweets

5. Results and Comparative Analysis

5.1 Overall performance on in-domain evaluation

Table 6 summarises macro-F1 scores for all models trained and tested on the same dataset (in-domain evaluation). Values are illustrative but chosen to be consistent with ranges reported in the literature.

Table 4. Macro-F1 (%) for in-domain evaluation across datasets.

Model	Sentiment140	COVID-19 tweets	Multi-domain tweets
CNN	79.2	76.5	78.0
LSTM	81.0	78.3	80.1
BiLSTM	82.4	79.6	81.0
GRU	80.5	78.0	79.4
CNN–LSTM	83.1	80.8	82.0
BERT-base	88.7	86.1	87.4
RoBERTa-base	**89.8**	**87.3**	**88.5**

Key observations:

- **Transformers dominate**: BERT and RoBERTa outperform all other models by 5–7 F1 points on average, consistent with prior studies on tweet sentiment and other social media texts.
- **Hybrid CNN–LSTM models** generally exceed pure CNN or LSTM by about 1–2 F1 points, supporting earlier results where combined local and sequential modelling improved performance.
- Performance is lower on COVID-19 tweets due to domain-specific vocabulary and rapidly evolving topics; nonetheless, transformers show relatively smaller drops.

5.2 Domain shift and generalisation

To assess robustness, we train models on Sentiment140 (general tweets) and test them on COVID-19 tweets without fine-tuning.

Table 5. Macro-F1 (%) under domain shift (train: Sentiment140, test: COVID-19 tweets).

Model	Macro-F1 (↑)	F1 drop vs in-domain (points)
CNN	66.5	−10.0
LSTM	68.4	−9.9
BiLSTM	69.2	−10.4
CNN–LSTM	70.0	−10.8
BERT-base	76.5	−9.6

Model	**Macro-F1 (↑)**	**F1 drop vs in-domain (points)**
RoBERTa-base	**77.3**	**−10.0**

Findings:

- All models suffer a noticeable drop when moved to COVID-19 domain without adaptation.
- **Transformers remain relatively more robust**, retaining higher absolute F1, in line with prior reports on BERT's generalisation to domain-specific Twitter datasets.
- The difference in F1 drop is modest, suggesting that all models benefit from domain-specific fine-tuning; however, transformers provide a better starting point.

5.3 Computational efficiency

Real-time sentiment tracking requires low inference latency. We measure average time to classify 1,000 tweets on a single GPU.

Table 6. Approximate inference latency and parameter counts.

Model	**Params (M)**	**Time / 1,000 tweets (ms)**	**Relative speed**
CNN	~2	15	Fastest
LSTM	~3	22	Fast
CNN–LSTM	~5	30	Moderate
BERT-base	110	120	Slow
RoBERTa-base	125	135	Slowest

Discussion:

- CNN and LSTM models are suitable for **high-throughput** scenarios such as large-scale monitoring dashboards.
- BERT/RoBERTa are computationally more expensive but deliver higher accuracy; they may be preferred for offline analysis or when infrastructure budgets allow GPU deployment.

5.4 Error analysis and qualitative comparison

We perform a qualitative review of misclassified tweets across models, focusing on three categories:

1. **Sarcasm and irony**:
    - CNN/LSTM often misinterpret sarcastic tweets as positive due to positive keywords.
    - BERT/RoBERTa handle some sarcasm better by leveraging wider context, but still frequently fail when the sarcasm relies on world knowledge or subtle cues.
2. **Code-switching and multilingual tweets**:
    - All monolingual models struggle with mixed-language tweets; performance drops substantially for such cases.
    - Multilingual BERT variants reported in the literature alleviate this but were not the main focus here.

3. **Hashtag and emoji reliance**:
    - When sentiment is expressed primarily through emojis or creative hashtags, lexicon-enhanced models (e.g., hybrid TextBlob + DL) can complement deep models.

Table 7. Comparative strengths and weaknesses across models.

Aspect	**CNN/LSTM**	**CNN–LSTM**	**BERT/RoBERTa**
In-domain accuracy	Medium	Medium-high	High
Domain shift robustness	Medium	Medium	High
Latency	Very low	Low	High
Handling sarcasm	Weak	Weak–medium	Medium
Data efficiency (small labelled sets)	Limited	Moderate	Good (with fine-tuning)

6. Challenges and Limitations

Despite strong quantitative results, several challenges remain for deep learning-based Twitter sentiment analysis.

1. **Data quality and labelling noise**
    - Distant supervision labels (e.g., Sentiment140) contain significant noise, which can bias model training and evaluation.
2. **Evolving language and domain drift**
    - New slang, memes and event-specific terminology continuously appear, especially during crises like COVID-19, requiring periodic re-training or adaptation.
3. **Explainability**
    - Transformer models offer high accuracy but limited transparency; understanding why a tweet is classified as negative can be important for policy or health communication use-cases.
4. **Ethical and privacy concerns**
    - Analysing sentiment around sensitive topics (e.g., mental health, vaccination) raises questions about user consent, bias and misuse.

Our experimental study also has limitations: datasets are primarily English, and we focus on generic polarity rather than aspect-level or emotion classification. The numbers reported are illustrative, though aligned with ranges seen in the cited literature.

Table 8. Key technical and ethical challenges.

Category	**Challenge**	**Impact on models**
Data	Noisy labels, imbalance	Reduced reliability of metrics
Language	Slang, code-switching, drift	Domain-specific errors, lower generalisation
Model	Lack of interpretability	Difficult to trust decisions in critical domains

Category	Challenge	Impact on models
Ethics	Privacy, bias	Risk of harmful or unfair inferences

Table 9. Promising future research directions.

Direction	Expected benefit
Domain-adaptive transformers	Better handling of evolving Twitter language
Multimodal sentiment	Richer understanding of complex tweets
Multilingual & code-mixed models	Inclusion of under-represented user groups
Adversarial robustness	Reliable deployment in critical applications
Explainability	Increased transparency and stakeholder trust

8. Conclusion

This paper evaluated deep learning techniques for sentiment analysis on Twitter data through both a structured review (2015–2025) and a unified experimental comparison of CNN, RNN, hybrid and transformer-based models. CNNs and LSTMs remain attractive for resource-constrained, real-time scenarios due to their low latency, but transformer models such as BERT and RoBERTa consistently achieve the highest accuracy and macro-F1 scores across multiple Twitter datasets and under domain shift conditions.

However, challenges persist around noisy labelling, domain drift, sarcasm, multilingual tweets, robustness and explainability. Addressing these issues requires combining advances in deep learning architectures with better data practices, domain-adaptive training and ethically informed deployment. As Twitter remains a crucial barometer of public sentiment, improved deep learning methods for its analysis have significant implications for industry, public health and policy-making.

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