# Table Summary of Research papers for literature survey

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| --- | --- | --- | --- | --- | --- | --- | --- |
| Sr No | Title of Paper (Year) | Dataset | Algorithms/ Methodologies | Evaluation Parameters | Advantages | Disadvantages | Future Scope |
| 1 | Comparison of Sentiment Analysis Algorithms using Twitter Dataset for Real time Analysis of Cricket Sport (2024) | 60,000  historical cricket tweets | SVM, Decision Tree, Random Forest | Accuracy, Precision, Recall, F1-score | SVM achieved the highest accuracy at 94.73% | SVM has high computational complexity | Optimize SVM, explore hybrid models, and analyze other sports |
| 2 | Cricket Twitter Data Sentiment Analysis and Prediction Exerted Machine Learning (2021) | Kaggle dataset (160k tweets) and live Twitter API | Logistic Regression, Random Forest | Accuracy, Precision, Recall,  F-measure | Logistic Regression was more accurate (79%) than Random Forest (69%) | Struggles with slang and misspellings | Add more algorithms and use specific match data for predictions |
| 3 | Exploring Twitter Sentiments for Predicting Match Outcomes in The Game of Cricket (2024) | Tweets from IPL 2022 & T20  World Cup 2022 | Naive Bayes, SVM, KNN,  Random Forest, XGBoost | Accuracy, Precision, Recall, F1-Score | KNN performed best with 56.7%  accuracy; SVC had the highest precision (75.6%) | The overall accuracy of the best model was low | Improve accuracy by using more granular data like player names |
| 4 | Memristive LSTM Network for Sentiment Analysis (2021) | IMDB and SemEval (Twitter) datasets | Memristor-base d LSTM (MLSTM)  hardware network | Accuracy, power consumption, hardware area | High accuracy (84.3% on  IMDB) ; very low power and small hardware footprint | Hardware-speci fic design may be less flexible than software | The simple design is easily expandable to other NLP tasks |
|  |  |  | Rule-based | Qualitative classification into 5  sentiment types | Effectively | Small dataset ; relies on manually created rules | Use |
|  | Sentiment Analysis on | 2,500 manually | NLP++ | interprets | human-based |
| 5 | Cricket Tweets using | annotated | language with | nuances like | methods to |
|  | NLP++ (2024) | cricket tweets | custom cricket | sarcasm and | analyze varied |
|  |  |  | dictionaries | emojis | texts |
|  | A review of sentiment | Survey of datasets like IMDB, Twitter, and SemEval | Surveys ML | Reviews papers using Accuracy and F1-score | Comprehensive |  | Explore generative models (ChatGPT) and Explainable AI (XAI) |
|  | analysis: tasks, | (SVM) and DL | overview of the | Does not |
| 6 | applications, and deep | (CNN, LSTM, | field; highlights | present a new |
|  | learning techniques | BERT) | the power of | implementation |
|  | (2025) | algorithms | DL/BERT |  |
| 7 | Research on the Application of Deep Learning-based BERT Model in Sentiment Analysis (2024) | SST2 (Stanford Sentiment Treebank) | DistilBERT with a Logistic Regression classifier | Accuracy, Precision, Recall, AUC | BERT  outperforms traditional models ; fine-tuning significantly improves performance | Performance is limited without fine-tuning ; can overfit on small datasets | Further research into fine-tuned BERT for practical applications |
| 8 | A Text Based Sentiment Analysis Model using  Bi-directional LSTM Networks (2021) | 23,485 Amazon e-commerce reviews | Bi-directional LSTM  (Bi-LSTM) with Word2Vec | Accuracy | Achieved high accuracy of 90.46% ;  captures context from both directions | Model performance is highly dependent on word vector quality | Incorporate self-attention mechanisms to improve text interpretation |