# Table Summary of Research papers for literature survey

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| Sr No | Title of Paper (Year) | Dataset | Algorithms/Methodologies | Evaluation Parameters | Advantage | Disadvantages | Future Scope |
| 1 | Ensemble-Based Framework for Fake News Detection in Social-Media (2025) | Social media datasets (unspecified) | Logistic Regression, SVM, Decision Tree, Ensemble methods | Accuracy, Precision, Recall, F1-score | High accuracy; interpretable; practical for real-time use | May not generalize well to multimodal data | Extend to include multimodal inputs (images/videos) |
| 2 | Social Media Spam Detection Using NLP in Machine Learning (2025) | Twitter/spam datasets (not specified) | Naive Bayes + TF-IDF, punctuation, hashtags | Accuracy, F1-score | Lightweight; interpretable; easy deployment | Lower performance for complex spam or fake content | Incorporate metadata and hybrid feature sets |
| 3 | FAKE NEWS DETECTION IN SOCIAL MEDIA USING ML (2023) | Social media datasets (unspecified) | Naive Bayes, SVM | Accuracy, Precision, Recall | Simple and interpretable; straightforward implementation | Limited capture of deep semantics | Blend classical models with explainable deep learning |
| 4 | Social Media Spam Detection Using Different Text Feature Selection Technique and Machine Learning (2022) | Twitter/spam datasets | TF-IDF, POS, Information Gain with SVM, ANN, Naive Bayes | Accuracy, Precision, Recall, F1-score | Hybrid features enhanced performance | ANN is less interpretable than SVM/NB | Build scalable, real-time systems |
| 5 | Transfer learning driven fake news detection and classification using interpretable ML (2025) | Benchmark social media datasets | Transfer learning + interpretable ML | Accuracy, Precision, Recall | Scalable and interpretable | Transfer models still resource-intensive | Develop lightweight yet interpretable transfer models |
| 6 | Interpretable Fake News Detection on Social Media (2023) | Posts and comments from social media | Interactive reasoning networks | Accuracy, Explainability metrics | Enables explanation via sentence-comment relationships | More complex than NB/SVM | Simplify reasoning networks for real-time use |
| 7 | A fuzzy-based multimodal approach for interpretable fake news detection (2025) | Social media (text + image) datasets | Fuzzy logic + multimodal text & image features | Accuracy, Precision, Recall | Combines modalities; interpretable via fuzzy rules | Requires availability of multimodal data | Extend fuzzy rules to audio/video modalities |
| 8 | Interpretable fake news detection with topic and deep variational models (2023) | News and social media datasets | Topic modeling + deep variational models | Accuracy, Explainability metrics | Extracts interpretable topic features | Deep models reduce transparency | Combined with lightweight classical models |
| 9 | Automated and Interpretable Fake News Detection With Explainable Artificial Intelligence (2022) | Social media/news datasets | Naive Bayes, Random Forest, Decision Tree ensembles + XAI methods | Accuracy, Precision, Recall, Explainability | Hybrid interpretable framework with explainable outputs | Higher computational cost for ensembles | Develop more efficient XAI techniques |
| 10 | SOCIAL MEDIA SPAM DETECTION USING DIFFERENT TEXT FEATURE SELECTION TECHNIQUE AND MACHINE LEARNING (2022) | Twitter/spam datasets | TF-IDF, POS, Information Gain + classical ML models | Accuracy, Precision, Recall | Hybrid features improve interpretability & performance | Lacks focus on metadata utilization | Introducing user metadata for better detection |