# PROJECT REPORT

## A Comparative Analysis of HANs, SVMs and XGBoost for Fake News Detection

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# Abstract

We consider the challenge of tackling the proliferation of fake news critical in today's dynamic socio-political landscape. Acknowledging its societal relevance and urgency, we aim to conduct a comparative analysis of machine learning models to identify those with optimal performance in correctly classifying this misinformation. For this purpose, we focus on the **WELFake dataset**. Traditional models like **SVM** demonstrate competitive performance in specific frameworks, achieving 99% accuracy with supervised FastText embeddings (Hashmi et al., 2024). The proposed approach combines **FastText** for text vectorization followed by a **Hierarchical Attention Network (HAN)** to model contextual and hierarchical features, while also evaluating **XGBoost** and **SVM** for comparative analysis.

# Research Papers Summary

Recent advancements in fake news detection highlight the evolution from traditional machine learning (ML) to hybrid deep learning (DL) frameworks. **Hashmi et al. (2024)** pioneered a hybrid model combining **FastText embeddings** with a **CNN-LSTM architecture**, achieving 99% accuracy on datasets like **WELFake** and **FakeNewsNet** by leveraging cross-modal attention and hierarchical syntactic patterns. Their integration of explainable AI (XAI) techniques, such as **LIME** and **Latent Dirichlet Allocation (LDA)**, enhanced model transparency—a critical requirement for real-world deployment.

**Sarasa-Cabezuelo et al. (2023)** conducted a comprehensive survey categorizing AI-driven detection methods into **deep learning**, **natural language processing (NLP)**, **ensemble learning**, and **graph-based approaches**, emphasizing the transition from rule-based systems to transformer models like **BERT** and knowledge graphs. Their work underscores the need for hybrid models that integrate social context and multi-modal data to address scalability and adversarial robustness challenges.

**Hu et al. (2022)** systematically reviewed DL paradigms, highlighting **CNN-LSTM hybrids** and **graph neural networks (GNNs)** for modeling propagation patterns. Their analysis demonstrated DL's superiority over traditional ML in capturing semantic dependencies and temporal-structural features, particularly on datasets like **Twitter15/16**, while advocating for weakly supervised learning to mitigate data scarcity.

**Granik and Mesyura (2017)** established a baseline using **Naive Bayes** on BuzzFeed's dataset, achieving 74% accuracy with bag-of-words. The authors advocate for preprocessing enhancements (e.g., **stop-word removal**, **stemming**) and dataset expansion to improve generalizability.

**Ozbay and Alatas (2020)** evaluated **more than 20 supervised algorithms** (e.g., J48, Random Forest) across multiple datasets, finding tree-based models (e.g., Decision Trees) superior on larger datasets like **ISOT** (96.8% accuracy).

## Problem Statement and Approach

**Problem Statement:** Given a news article, determine if it is legitimate or fake.

We employ a comparative framework to evaluate the efficacy of hierarchical neural architectures against traditional machine learning models for fake news detection on the **WELFake dataset**, comprising 72,134 web and social media articles labeled as "fake" or "real". We use **FastText** for word-level embeddings to capture semantic relationships in the preprocessing phase itself, to convert the text data into vector embeddings. For our first model, we plan to use **Hierarchical Attention Network (HAN)** designed to model article-level contextual hierarchies through sentence and word-level attention layers. For baseline comparison, we plan to implement **Support Vector Machine (SVM)** and **XGBoost** with hyperparameter tuning. Text preprocessing includes **lemmatization**, **stop-word removal**, and normalization to mitigate noise, while model performance is assessed using **accuracy**, **precision**, **recall**, **F1-score**, and **Matthews Correlation Coefficient (MCC)** to address class imbalance. We plan to use a cross-validation strategy to ensure robustness. The approach draws on established methodologies: FastText's utility in hybrid architectures (Hashmi et al., 2024), SVM's robustness in feature-engineered setups (Sarasa-Cabezuelo et al., 2023), and XGBoost's ensemble efficacy (Ozbay & Alatas, 2020), while addressing scalability gaps identified in shallow models like Naive Bayes (Granik & Mesyura, 2017).

## References


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