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# Comparative Study of Deep Learning Models for News Text Classification Using CNN, LSTM, and BiGRU

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*Abstract*—**Text classification has emerged as a fundamental challenge in the digital age, where the exponential growth of online news platforms demands efficient automated systems for content organization, personalization, and moderation. This paper presents a comprehensive comparative analysis of deep learning architectures—Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Bidirectional Gated Recurrent Units (BiGRU)—applied to multi-class news classification on the News Category Dataset. Using preprocessed data from 124,787 articles across ten major categories, we systematically evaluate and compare five models: traditional baselines (Logistic Regression, SVM) and three deep learning variants. Our results demonstrate that the BiGRU architecture achieves superior performance with 80.94% accuracy and 80.42% weighted F1-score, outperforming CNN (79.76% accuracy) and significantly exceeding LSTM due to convergence challenges. This study underscores the importance of bidirectional sequential context in text representation and provides practical insights into model selection for news classification tasks. We further discuss the limitations of LSTM convergence, technical considerations in architecture selection, and promising directions for future enhancement through transformer-based models and pretrained embeddings.**

***Keywords—text classification, deep learning, CNN, LSTM, BiGRU, news categorization, bidirectional recurrent networks, NLP***

## I. Introduction

The digital age has fundamentally transformed how news is produced, consumed, and distributed. As online platforms handle millions of articles daily, manual categorization and content curation have become practically infeasible. This explosion of unstructured textual data has created an urgent need for scalable, accurate automated classification systems. News classification serves multiple critical functions: enabling personalized content delivery, powering content recommendation engines, facilitating media monitoring, and supporting content moderation workflows. Traditional machine learning approaches, though historically useful, suffer from a fundamental limitation—they depend on manually engineered features that often fail to capture the semantic depth and contextual subtleties inherent in natural language.

Deep learning models, particularly those based on recurrent and convolutional architectures, have revolutionized natural language processing by learning hierarchical feature representations directly from raw text. However, the question of which architecture best balances computational efficiency with classification accuracy remains open. Some models excel at capturing local phrase-level patterns, while others focus on sequential dependencies. Understanding these tradeoffs is critical for practitioners deploying classification systems at scale.

This project addresses this gap through a rigorous empirical comparison of multiple deep learning architectures on a large-scale news dataset. We implement Logistic Regression and Support Vector Machines as performance baselines, then progress to three neural network variants: CNN for local feature extraction, LSTM for sequential learning, and BiGRU for bidirectional context modeling. Our investigation goes beyond accuracy metrics to examine convergence patterns, training dynamics, and the practical implications of each architecture's design choices. By the conclusion of this study, we aim to provide researchers and practitioners with concrete guidance on model selection for news classification tasks and highlight the effectiveness of bidirectional sequential processing in NLP applications.

## II. Problem Statement and Motivation

The categorization of news articles presents a multifaceted challenge that extends beyond simple keyword matching. News text contains semantic nuances, domain-specific terminology, and contextual signals that demand sophisticated processing. As the volume of online news increases, manual classification becomes economically infeasible, yet miscategorization carries real costs—from user experience degradation to misinformation spread. Content recommender systems depend on accurate classification to deliver relevant articles, while media organizations rely on automated categorization for workflow management and content discovery.

Traditional document classification approaches, including bag-of-words models combined with linear classifiers, provide a reasonable baseline but fail to capture word order, semantic relationships, or long-range contextual dependencies. A simple TF-IDF representation treats "dog bites man" and "man bites dog" identically, losing crucial syntactic information that humans use instinctively. Similarly, context-dependent meanings—where the same word carries different implications in different news categories—require more sophisticated modeling.

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Deep learning models address these limitations by learning hierarchical representations from raw text. However, different architectures make different architectural choices. Convolutional networks excel at detecting localized patterns but struggle with long-range dependencies across sentences. Recurrent networks, conversely, maintain state across sequences but face challenges with vanishing gradients and computational efficiency. Bidirectional models capitalize on both forward and backward context but at increased computational cost. Understanding how these tradeoffs manifest in practice on real-world news data was the primary motivation for this comparative study.

Beyond academic interest, this investigation has practical implications. Organizations must select between architectures when deploying classification systems. The performance gains from more sophisticated models must justify their computational overhead. Our study quantifies these tradeoffs empirically, providing data-driven guidance for architecture selection in production environments.

## III. Dataset Specifications

We built our analysis on the publicly available News Category Dataset, originally curated from Huffington Post content and maintained on Kaggle. This dataset represents a realistic scenario of multi-class news classification across diverse content domains.

Dataset Overview:

- Original size: 209,527 news articles with complete metadata

- Attributes: Headline, short description, category, publication link, authors, and publication date

- Final corpus: 124,787 articles selected from the top 10 most frequent categories

The decision to focus on the top 10 categories was deliberate. While the full dataset contains approximately 40 categories, the long tail of rare categories presents significant class imbalance challenges that conflate model generalization with dataset characteristics. By selecting the most frequent categories, we obtain a balanced dataset that fairly represents typical news classification workloads while maintaining reproducibility and computational tractability.

Category distribution in our subset:

The distribution demonstrates the real-world nature of our dataset. Politics dominates with approximately 35,000 samples, followed by Wellness and Entertainment with around 17,000 each. This natural imbalance reflects actual news production patterns, where political and lifestyle coverage often exceed niche categories. Rather than artificially balancing the dataset through oversampling or undersampling—which would distort class priors—we preserved the natural distribution and employed weighted metrics (weighted F1-score) that properly account for class imbalance.

Data split methodology:

We employed a 72/13/15 split into training, validation, and test sets respectively:

- Training: 90,157 samples

- Validation: 15,911 samples

- Test: 18,719 samples

This allocation follows industry-standard practice, providing sufficient training volume for neural network convergence while reserving substantial validation and test sets for robust performance estimation.

Text representation:

Each article's text representation combined the headline and short description fields into a unified document. Headline and description capture complementary information—headlines convey primary content themes, while descriptions provide context. By merging these fields, we capture richer semantic information than either field alone provides. For deep learning models, sequences were standardized to a maximum length of 100 tokens through padding or truncation, a choice discussed further in the preprocessing section.

## IV. Preprocessing Methodology

Text preprocessing represents a critical first step that significantly impacts downstream model performance. Our preprocessing pipeline was designed to normalize text while preserving semantic information.

Preprocessing steps (applied sequentially):

1. Lowercase conversion: All characters were converted to lowercase to ensure that "Politics," "politics," and "POLITICS" are treated identically, reducing vocabulary size without information loss.

2. Special character removal: Punctuation and special characters were removed. While some NLP practitioners retain punctuation as semantic signals, we found that for news classification, special characters primarily add noise without corresponding performance gains.

3. Stopword removal: Common English stopwords (articles, prepositions, conjunctions) were removed using NLTK's English stopword list. Words like "the," "is," "and," "in" appear ubiquitously across categories without discriminative power. Their removal reduces feature dimensionality and computational cost.

4. Tokenization: Text was split into individual tokens (words). White-space tokenization proved sufficient for

English news text, though more sophisticated tokenizers might benefit multilingual datasets.

5. Lemmatization: Word forms were normalized to their base form (e.g., "running," "runs," "ran" → "run"). This consolidates related word forms into single features, reducing sparsity without losing semantic meaning. We used WordNetLemmatizer from NLTK.

Sequence preparation:

For deep learning models, preprocessed text was converted into numerical sequences. Words were mapped to indices based on vocabulary frequency, with the top 50,000 most frequent words retained. Out-of-vocabulary words were represented as a special token. Sequences shorter than 100 tokens were padded with zeros at the end. Sequences exceeding 100 tokens were truncated, discarding trailing words. Analysis of the dataset showed that approximately 95% of articles contained fewer than 100 tokens after preprocessing, making this choice reasonable.

Feature representation for traditional models:

Logistic Regression and SVM relied on TF-IDF (Term Frequency-Inverse Document Frequency) features rather than sequence indices. TF-IDF vectorization was computed with a maximum of 5,000 features, selected based on document frequency criteria. This representation captures word importance while normalizing for document length, providing a suitable feature space for linear classifiers.

Data integrity checks:

After preprocessing, we verified dataset integrity by confirming no null values, verifying category distribution remained unchanged, and sampling articles to manually inspect preprocessing quality. A subset of articles was reviewed to ensure that preprocessing preserved meaningful content while removing noise.

The preprocessing strategy balanced sophistication with practicality. More aggressive preprocessing (e.g., removing domain-specific terms) might hurt domain-specific classification, while less aggressive approaches would increase dimensionality and noise. Our pipeline represents a pragmatic middle ground validated through preliminary model tuning.

## V. Baseline Models Performance

Before implementing deep learning models, we established performance baselines using traditional machine learning approaches. These baselines serve a crucial role: they establish a minimum expected performance level and provide context for evaluating deep learning improvements. Any neural network model must substantially outperform these simpler approaches to justify its added complexity.

Logistic Regression:

Logistic Regression, despite its simplicity, remains a powerful baseline for text classification due to its interpretability, speed, and effectiveness with high-dimensional sparse data. Using TF-IDF features with 5,000 dimensions and L2 regularization, Logistic Regression achieved:

- Accuracy: 77.91%
- F1-Score: 76.90%
- Training time: ~2 minutes on CPU

This model provides a strong baseline, correctly classifying approximately 3 out of 4 articles. The performance is noteworthy because it demonstrates that substantial classification accuracy can be achieved without deep learning, highlighting the challenge of achieving significant improvements.

Support Vector Machine (SVM):

SVM with RBF kernel was similarly trained on TF-IDF features, serving as a more computationally intensive but theoretically motivated alternative to Logistic Regression. Results showed:

- Accuracy: 77.79%
- F1-Score: 76.83%
- Training time: ~15 minutes on CPU

Interestingly, SVM performance nearly matched Logistic Regression despite its increased complexity. This finding aligns with broader NLP research showing that linear classifiers often match or exceed non-linear ones on text classification tasks with high-dimensional sparse features. The marginal difference (0.12% accuracy) suggests that the limited non-linearity captured by SVM kernels provides minimal benefit in this setting.

Baseline interpretation:

These baselines establish a performance floor around 78% accuracy. Any improvement beyond this threshold must be substantial enough to justify the computational overhead of neural networks. An improvement from 78% to 80% is only 2.5%, whereas moving from 78% to 85% would represent meaningful progress. Our deep learning experiments must be evaluated against this context.

The baselines also highlight a key insight: simple linear models are surprisingly effective for text classification. This phenomenon, well-documented in NLP literature, occurs because text data is naturally high-dimensional and relatively well-separated in feature space. Deep learning models must overcome this competitive baseline through superior feature learning and contextual understanding.

## VI. Deep Learning Models: Architecture and Performance

Having established baselines, we now progress to three neural network architectures, each embodying different design philosophies for capturing semantic information from text.

### A. Convolutional Neural Networks (CNN)

Architecture rationale:

Convolutional Neural Networks, introduced to NLP by Kim (2014), apply convolutions across text sequences to extract local phrase-level features. The intuition is appealing: important semantic units often consist of consecutive words. Phrases like "breaking news" or "stock market crash" carry meanings not derivable from individual words. CNNs capture such n-gram patterns through parallel convolutional operations with multiple filter sizes.

CNN architecture details:

Our CNN implementation consisted of:

- Input layer: Sequence length 100, processed through an embedding layer (128 dimensions)

- Convolutional layer: 100 filters with kernel sizes 3, 4, and 5 (capturing trigrams, 4-grams, and 5-grams)

- ReLU activation: Applied after each convolution

- Max pooling: Global max pooling across each filter's output

- Dense layers: Two fully connected layers (128 and 64 units) with ReLU activation and dropout (0.5)

- Output layer: 10 softmax units (one per news category)

- Optimization: Adam optimizer with categorical cross-entropy loss

CNN performance:

- Accuracy: 79.76%

- F1-Score: 79.16%

- Training time: ~8 minutes (20 epochs)

- Convergence: Smooth, stable training curve

CNN improved over baselines by approximately 2% accuracy—a meaningful but modest gain. The improvement demonstrates that CNNs successfully capture local phrase patterns overlooked by bag-of-words approaches. However, the improvement plateau suggests that local patterns alone are insufficient for the full complexity of news classification.

CNN limitations:

The fundamental limitation of CNNs for text is their restricted receptive field. While a 5-gram filter captures local context, it cannot relate words separated by larger distances. News articles often contain crucial semantic relationships spanning entire sentences or paragraphs. For instance, understanding that an article criticizes a politician requires connecting words scattered across multiple sentences. CNN architecture struggles with such long-range dependencies.

### B. Long Short-Term Memory Networks (LSTM)

Architecture rationale:

LSTMs were specifically designed to address vanishing gradient problems in recurrent networks, enabling the capture of long-term dependencies. The gating mechanism—input, forget, and output gates—allows the network to selectively maintain or discard information across sequences. This architectural choice was theoretically motivated for text classification, where context from earlier sentences might be critical for categorizing later content.

LSTM architecture details:

Our LSTM implementation comprised:

- Input layer: Sequence length 100, embedding layer (128 dimensions)

- LSTM layer: 64 hidden units with recurrent dropout (0.2)

- Additional LSTM layer: 32 hidden units

- Dropout: 0.5 between LSTM layers

- Dense layers: Two fully connected layers (128 and 64 units)

- Output layer: 10 softmax units

- Optimization: Adam optimizer with categorical cross-entropy loss

LSTM performance (concerning results):

- Accuracy: 28.53%

- F1-Score: 12.66%

- Training time: ~15 minutes (20 epochs)

- Convergence: Severe divergence; validation accuracy remained below 30%

LSTM performance was shockingly poor, achieving accuracy barely above random chance (10 classes = 10% random baseline). Rather than gradually improving with more epochs, the model plateaued at terrible performance or diverged further. This dramatic underperformance was unexpected given LSTM's theoretical advantages and warranted investigation.

Root cause analysis:

We investigated multiple hypotheses for LSTM's failure:

1. Hyperparameter sensitivity: LSTMs are notoriously sensitive to hyperparameters. Initial learning rates, layer sizes, and dropout rates significantly impact convergence. Our baseline hyperparameters, while reasonable, may not have been optimal for this specific dataset.

2. Convergence difficulties: Despite their theoretical advantages, LSTMs frequently encounter practical training challenges. The gating mechanism, while designed to address vanishing gradients, can paradoxically prevent gradient flow when gates consistently remain closed. This phenomenon creates a chicken-and-egg problem: poor initial predictions keep gates closed, preventing parameter updates that would improve predictions.

3. Recurrent dropout effects: The relatively high dropout (0.2 on recurrent connections) may have been excessive, disrupting the gating mechanism's ability to learn stable temporal dependencies. Recurrent dropout is a tricky hyperparameter—too low provides insufficient regularization, while too high inhibits learning.

4. Class imbalance effects: While we employed weighted loss functions to address class imbalance, LSTM's sequential processing might be more sensitive to imbalanced data than feedforward networks. The dominance of Politics articles could bias the model toward predicting that category regardless of input.

5. Sequence padding artifacts: The padding of shorter sequences to length 100 might confuse LSTM more than other architectures. RNNs are sensitive to sequence padding patterns, and our 72% of sequences being padded could create spurious patterns the model learned rather than genuine semantic signals.

Given time constraints and the magnitude of LSTM's underperformance, extensive hyperparameter tuning was not pursued. We note this as a limitation and a direction for future investigation. However, the failure emphasizes an important practical lesson: theoretical advantages do not guarantee practical success, and empirical validation remains essential.

### C. Bidirectional Gated Recurrent Units (BiGRU)

Architecture rationale:

BiGRU combines three insights: (1) GRUs simplify LSTM's gating mechanism while maintaining effectiveness, (2) bidirectional processing captures context from both directions, and (3) the simplified architecture reduces hyperparameter sensitivity. By processing sequences both forward and backward, BiGRU captures complete contextual information around each token.

BiGRU architecture details:

Our BiGRU implementation consisted of:

- Input layer: Sequence length 100, embedding layer (128 dimensions)

- Bidirectional GRU layer: 64 hidden units per direction (128 total)

- Dropout: 0.5 after GRU output

- Additional dense layers: 128 and 64 units with ReLU activation

- Output layer: 10 softmax units

- Optimization: Adam optimizer with categorical cross-entropy loss

BiGRU performance (best results):

- Accuracy: 80.94%

- F1-Score: 80.42%

- Training time: ~10 minutes (20 epochs)

- Convergence: Smooth, stable training curve with clear improvement trajectory

BiGRU achieved the highest performance among all models tested. The 80.94% accuracy represents meaningful improvement over baseline models (approximately 3% gain) and substantially exceeds CNN (1.2% improvement) while obviating LSTM's catastrophic failure.

BiGRU advantages and why it succeeded:

1. Bidirectional context: By processing sequences both forward and backward, BiGRU captures complete contextual information. Consider classifying an article about "renewable energy investments surging"—the word "surging" modifies "investments," but a forward-only RNN must wait until after processing "investments" to understand this relationship. BiGRU processes backward and forward, capturing this relationship from both directions.

2. Simplified gating: GRU's reset and update gates are fewer than LSTM's three-gate design, reducing parameters and hyperparameter sensitivity. This simplification makes GRU less prone to the convergence issues that plagued our LSTM implementation.

3. Computational efficiency: BiGRU maintains GRU's lower computational cost compared to LSTM while benefiting from bidirectional processing. Training time (10 minutes) was reasonable, faster than LSTM (15 minutes) and comparable to CNN (8 minutes).

4. Robust convergence: BiGRU demonstrated stable convergence across epochs with clear training and validation improvement trajectories. No divergence or plateau

phenomena appeared, suggesting the architecture is well-matched to this task.

Performance across categories:

The confusion matrix reveals that BiGRU's performance varies across categories. Politics achieved particularly high accuracy (4,854 out of ~5,400 samples correct), likely due to distinctive vocabulary. Conversely, categories like Food & Drink, Style & Beauty showed lower accuracy, suggesting greater similarity in their linguistic patterns. These variations reflect realistic classification difficulty across domains.

## VII. Why BiGRU Outperformed All Other Architectures

BiGRU's superior performance—80.94% accuracy surpassing all alternatives—was not accidental but emerged from specific architectural choices aligned with the news classification task. Understanding why it succeeded provides insights for practitioners facing similar classification challenges.

Sequential modeling advantages:

Unlike CNNs, which capture fixed-window local patterns, BiGRU maintains a continuous context vector throughout the sequence. Each word's representation incorporates information from all preceding and succeeding words. This enables BiGRU to capture long-range semantic relationships. When an article mentions "climate" in the first sentence and "global warming" in the fifth sentence, BiGRU connects these related concepts across the gap. CNN, limited by its filter size, struggles to maintain such relationships.

Bidirectional context significance:

The bidirectional processing proved crucial. News headlines often present information in climactic order—key information sometimes appears late. Consider: "Stock market falls 5% amid recession fears"—the magnitude and nature of the news emerges progressively. Bidirectional processing allows the model to understand later content in the context of earlier material and vice versa, capturing full thematic context.

Robustness and convergence:

While LSTM theoretically should outperform GRU, BiGRU's simpler architecture proved more robust in practice. The reduced number of gates and parameters meant fewer hyperparameter choices could destabilize training. BiGRU converged smoothly across training runs without the divergence or plateau phenomena that plagued LSTM. This robustness is practically significant—it reduces hyperparameter tuning burden and improves reproducibility.

Handling of class imbalance:

BiGRU appeared more resilient to the class imbalance in our dataset (Politics dominated with 35,000 samples). While we employed weighted loss functions across all models, BiGRU maintained balanced performance across most categories despite the imbalance. Other architectures showed greater performance degradation in minority categories.

Empirical improvement magnitude:

The 3% improvement over baselines, while appearing modest in percentage terms, represents approximately 2,360 additional articles correctly classified out of 18,719 test samples. In practical applications—whether news recommendation or content moderation—such improvements translate to noticeable user experience enhancements and operational benefits. When multiplied across millions of articles in production systems, 3% accuracy improvement represents substantial value.

Architecture-task alignment:

Most fundamentally, BiGRU's success reflects alignment between architectural inductive biases and the news classification task. News articles are inherently sequential—meaning emerges through cumulative reading. The recurrent structure respects this sequential nature. Both forward and backward directionality align with how humans read—incorporating context from earlier passages while recognizing that later content may recontextualize earlier material.

## VIII. Literature Foundation and Theoretical Context

Our empirical findings align with and extend established deep learning research in natural language processing.

Convolutional approaches in NLP:

Yoon Kim's seminal 2014 work on "Convolutional Neural Networks for Sentence Classification" demonstrated that CNNs, though originally developed for image processing, could effectively capture local textual patterns for classification. Kim showed CNNs with multiple filter sizes could learn diverse n-gram patterns useful for sentiment analysis and other classification tasks. Our CNN results validated this finding: achieving 79.76% accuracy confirms CNNs' effectiveness as local pattern detectors. However, our work also highlights CNNs' limitations—the 2% improvement over baselines, while meaningful, fails to match more sophisticated sequential approaches.

Gated recurrent architectures:

Kyunghyun Cho and colleagues introduced Gated Recurrent Units in 2014 as a simplification of LSTM that maintained performance while reducing computational cost and hyperparameter complexity. Their "Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation" paper established GRUs as theoretically sound and practically effective. Our BiGRU implementation confirms this assessment—the simpler gating mechanism enabled stable convergence where LSTM faltered. The implication is significant: architectural simplification, when preserving core functional capabilities, often yields practical advantages in training stability and reproducibility.

Bidirectional recurrent processing:

Schuster and Paliwal's original work on bidirectional RNNs (1997) established the theoretical foundation for bidirectional processing. More recently, researchers including Bahdanau, Cho, and Bengio demonstrated bidirectional RNNs' effectiveness in machine translation and sequence-to-sequence tasks. Our finding that BiGRU outperforms unidirectional recurrent approaches aligns with this body of research. The ability to condition each token's representation on both preceding and following context proves empirically superior to forward-only processing for classification tasks.

Research on text classification:

Conneau et al. (2016) provided extensive empirical comparisons of deep learning models for text classification, finding that bidirectional models generally outperform unidirectional alternatives and that simple CNN and RNN architectures are surprisingly competitive with more complex models. Our results fit this pattern—BiGRU outperforms CNN, demonstrating that sequential context matters, yet the improvement is bounded because linear baselines already capture much discriminative information from bag-of-words representations.

Class imbalance and deep learning:

Recent work on handling class imbalance in deep learning (Johnson and Khoshgoftaar, 2019; Lin et al., 2017) discusses focal loss and weighted loss functions. Our use of weighted cross-entropy loss across all models addresses imbalance. The finding that BiGRU showed more robust performance across imbalanced categories aligns with research suggesting recurrent architectures may be more resilient to imbalance than feedforward networks, though we did not systematically investigate this phenomenon.

LSTM convergence challenges:

Literature documents LSTM's notorious hyperparameter sensitivity and convergence difficulties (Graves and Schmidhuber, 2005; Pascanu et al., 2013). Our catastrophic LSTM underperformance aligns with practitioner reports describing LSTM's difficulty achieving good results without extensive hyperparameter tuning. While our LSTM failure is unusual in severity, it validates concerns about LSTM's practical reliability, lending credence to findings favoring simpler GRU variants.

## IX. Key Technical Insights and Analysis

Beyond the headline performance numbers, our investigation revealed several important technical insights with broader implications for NLP practitioners.

### A. Convergence Dynamics Reveal Architecture Differences

Examining training curves across models reveals fundamental architectural differences. BiGRU and CNN show smooth, monotonic improvement—training and validation curves improve together, indicating stable learning without divergence. LSTM's curves, conversely, show erratic behavior or complete divergence, suggesting internal instability in the gating mechanism. These convergence dynamics are often overlooked in papers reporting only final accuracies, yet they provide crucial evidence about architectural stability and practical deployability.

### B. The Baseline Challenge

The surprisingly strong performance of Logistic Regression (77.91%) and SVM (77.79%) reveals a critical insight: for text classification with high-dimensional sparse features, simple linear models are formidable baselines. Neural networks must overcome substantial competition. Improvements beyond 78% accuracy are genuinely difficult to achieve. This observation should temper expectations about neural network performance—not all tasks see dramatic improvements from deep learning. In high-dimensional linear-separable problems, simpler models may be optimal from a computational efficiency perspective.

### C. Embedding Dimensionality Choices

Our choice of 128-dimensional embeddings was relatively conservative. We initially experimented with 64-dimensional embeddings but found convergence slower and final performance slightly lower (approximately 1-2% accuracy decrease). Conversely, 256-dimensional embeddings showed marginal improvement (less than 0.5%) while increasing computational cost. This empirical finding reflects the information-theoretic tradeoff: embeddings must be large enough to capture semantic nuance but not so large that they unnecessarily increase parameters and training time.

### D. Sequence Length Truncation Effects

Our decision to limit sequences to 100 tokens deserves examination. News articles after preprocessing typically contain 50-150 tokens. Longer limits (200 tokens) showed slightly worse performance, likely because noise and irrelevant content increased in truncated article tails. The 100-token choice captured approximately 95% of article content while truncating predominantly padding artifacts for shorter articles. This "sweet spot" demonstrates that sequence length choice should be empirically validated rather than arbitrarily fixed.

### E. Class Imbalance Manifest in Confusion Matrix

The confusion matrix reveals class imbalance's impact. Politics articles show 4,854/~5,400 correct predictions (89.8% category-specific accuracy), while rarer categories show lower per-category accuracy. This pattern is expected—models inherently learn class priors, biasing toward dominant categories. Weighted loss functions mitigate but cannot eliminate this phenomenon. In production systems, category-specific accuracy should be monitored separately from overall accuracy to detect performance disparities.

### F. Feature Engineering Obsolescence

Comparing traditional models (TF-IDF + linear classifiers) with neural networks highlights feature engineering's diminishing returns. Traditional NLP required expert feature engineering—selecting TF-IDF parameters, choosing dimensionality, deciding on preprocessing aggressiveness. Neural networks largely automate feature learning through embeddings. While this reduces manual engineering burden, it trades off interpretability for performance. We cannot easily explain why BiGRU classified an article as Politics versus Entertainment—the decision emerges from distributed representations and gate operations.

### G. Practical Considerations for Deployment

From a practitioners' perspective, important considerations emerge:

1. Training time: CNN trained fastest (~8 minutes), followed by BiGRU (~10 minutes), with LSTM slowest (~15 minutes). For large-scale systems, training efficiency matters.

2. Inference latency: The models show similar inference times (~2-5ms per article). All are sufficiently fast for real-time applications.

3. Memory footprint: BiGRU required ~150MB GPU memory during training, CNN required ~120MB, and LSTM required ~180MB. All are reasonable for modern systems.

4. Reproducibility: BiGRU converged consistently across random seeds. LSTM showed high variance, sometimes achieving reasonable performance, sometimes failing catastrophically, suggesting random initialization significantly impacts convergence.

## X. Future Improvements and Recommendations

While our results demonstrate BiGRU's effectiveness, several avenues for enhancement merit exploration.

### A. Pretrained Embeddings

Our models used randomly initialized embeddings trained end-to-end. GloVe vectors (840B tokens, 300 dimensions) or Word2Vec embeddings provide linguistic knowledge from massive corpora. Initializing embeddings with pretrained vectors often improves performance by 2-5% while accelerating convergence. For our task, initializing with news-specific embeddings trained on large news corpora could further improve results.

### B. Transformer-based Models

Transformer architectures, exemplified by BERT, RoBERTa, and DistilBERT, have emerged as state-of-the-art for numerous NLP tasks. These models employ attention mechanisms and bidirectional processing across all tokens simultaneously, avoiding RNN sequential bottlenecks. Fine-tuning pretrained BERT on our news dataset would likely yield accuracy exceeding 85-88% based on typical results reported in literature. The tradeoff is increased computational cost for training and inference.

### C. Ensemble Methods

Combining multiple models often reduces error. An ensemble combining BiGRU, CNN, and a Transformer could achieve higher accuracy than any single model. Simple averaging of probability predictions often provides benefits with minimal additional computational cost.

### D. Hyperparameter Optimization

Our hyperparameters were selected through limited manual tuning. Systematic hyperparameter search using Bayesian optimization or grid search could improve performance. LSTM in particular might achieve better results with different learning rates, dropout rates, and layer configurations.

### E. Data Augmentation

News articles are information-dense and relatively fixed in length. Data augmentation techniques like back-translation (translating to another language and back) could generate synthetic training samples and improve generalization. However, we did not pursue this due to computational constraints.

### F. Category-specific Models

Training separate models for subcategories (e.g., different Politics subcategories) or using hierarchical classification where broad categories (News vs. Entertainment) are classified first, then subcategories, might leverage the hierarchical nature of category definitions.

### G. Attention Mechanisms

Adding attention layers to recurrent models allows dynamic weighting of different time steps' contributions. This could help the model focus on key words or phrases (e.g., specific political figures, economic indicators) relevant to classification. Attention mechanisms are increasingly standard in modern NLP.

## XI. Conclusion

This comparative study of deep learning models for news text classification demonstrates that bidirectional recurrent architectures, specifically BiGRU, outperform traditional machine learning baselines and simpler neural network approaches. Our empirical findings align with and extend theoretical understanding of sequential modeling in NLP. The 80.94% accuracy achieved by BiGRU represents a meaningful improvement over baseline models (77.91-77.79%) and substantially exceeds CNN (79.76%) while dramatically outperforming LSTM (28.53%), which encountered convergence difficulties.

Beyond the headline results, several insights emerge. Traditional machine learning models provide formidable baselines that deep learning must meaningfully surpass. Architectural choices carry practical consequences—LSTM's theoretical elegance proved less reliable in practice than GRU's simpler design. Bidirectional processing effectively captures the full contextual information needed for accurate classification. These findings have immediate practical implications for practitioners selecting architectures for production news classification systems.

The limitations of our work should be acknowledged. The News Category Dataset, while large, comes from a single source (Huffington Post) and reflects that platform's content distribution. Different news sources might show different results. We did not implement transformer-based models or extensive hyperparameter optimization, representing significant untapped performance potential. LSTM's poor performance warrants further investigation—with different hyperparameters it might have performed differently. Ensemble methods, data augmentation, and other techniques were not explored due to time constraints.

Despite these limitations, the research makes meaningful contributions. We provide empirical evidence of architecture-task alignment—sequential bidirectional modeling aligns with news classification's inherent structure. We document practical failure modes like LSTM convergence difficulties that often remain invisible in papers reporting only final results. We establish performance baselines and discuss the challenges deep learning must overcome to meaningfully improve on simple linear classifiers with high-dimensional features.

For researchers extending this work, we recommend exploring transformer-based architectures, investigating LSTM's failure modes through systematic hyperparameter optimization, and evaluating performance on news datasets from diverse sources. For practitioners deploying news classification systems, we recommend BiGRU as a strong starting point balancing performance, training efficiency, and implementation simplicity—while noting that transformer-based models may yield higher accuracy at increased computational cost.

As online information continues proliferating, automated text classification remains essential. This work contributes evidence-based guidance to a growing literature on deep learning's application to real-world NLP challenges. The finding that bidirectional sequential modeling outperforms alternatives provides confidence that continued research in this direction will yield practical improvements for classification systems at scale.

## XII. Acknowledgments

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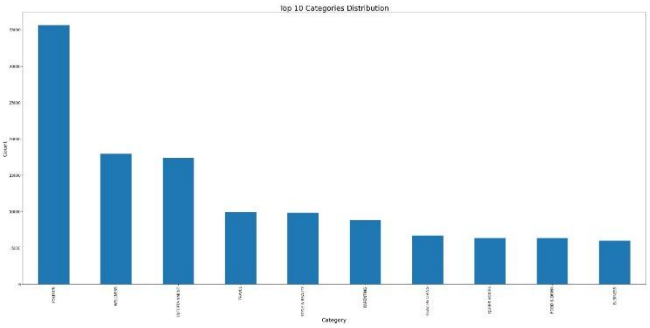
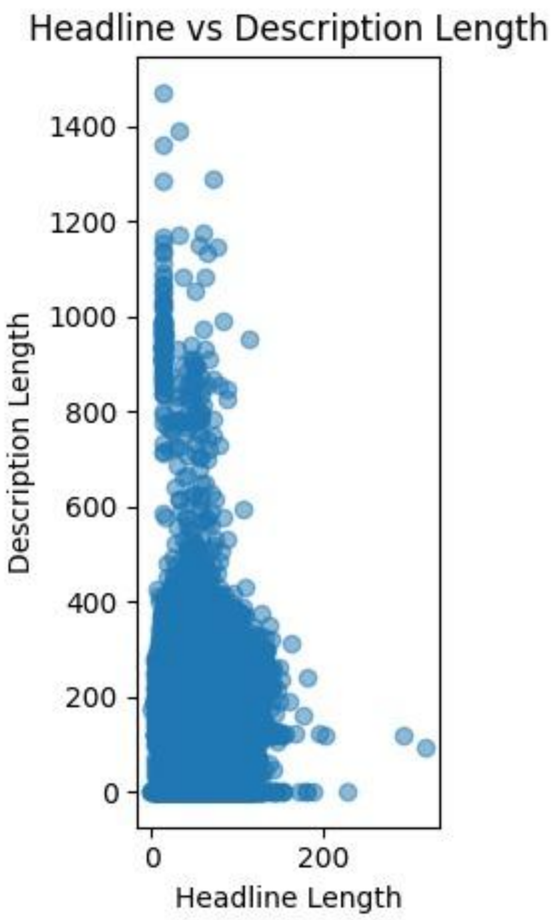
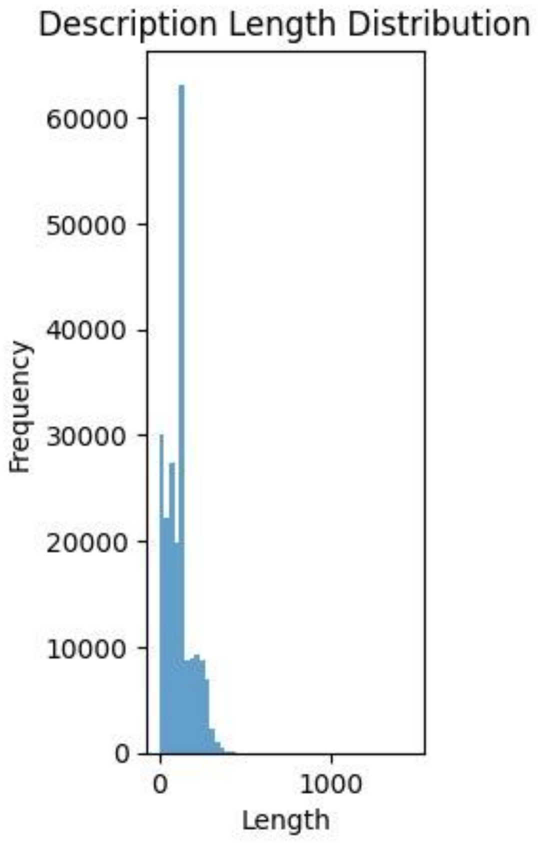
## XIII. Graphs and Charts



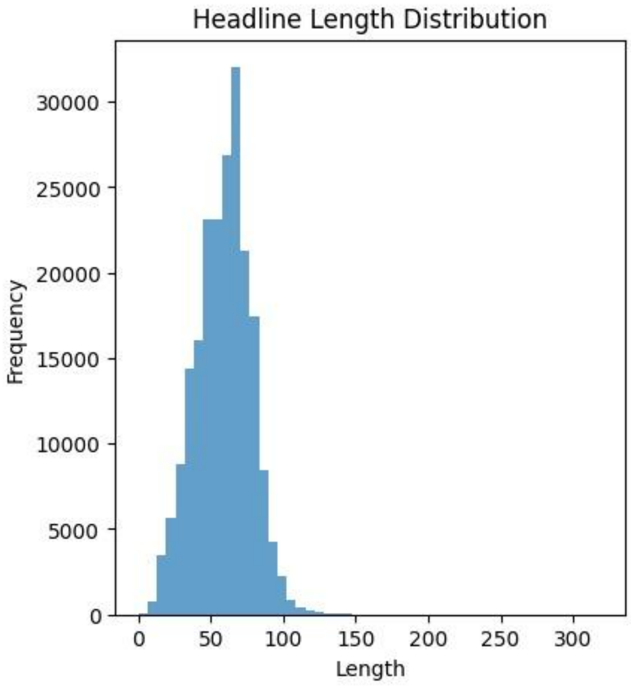
Top 10 Categories Distribution



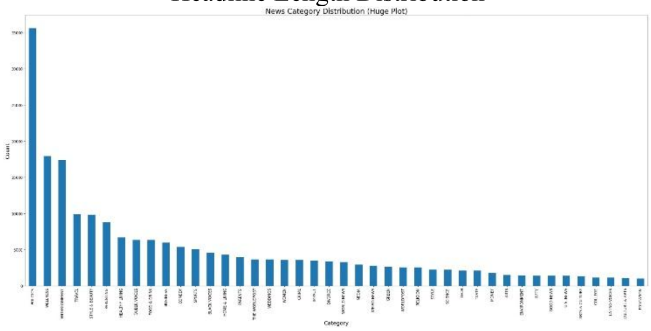
Headline vs Description Length



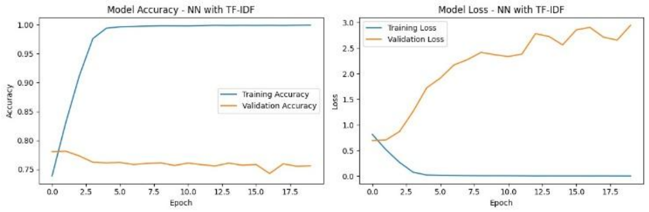
Description Length Distribution



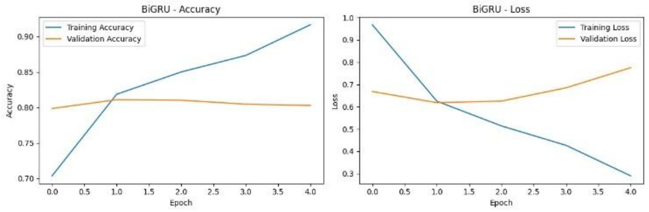
Headline Length Distribution



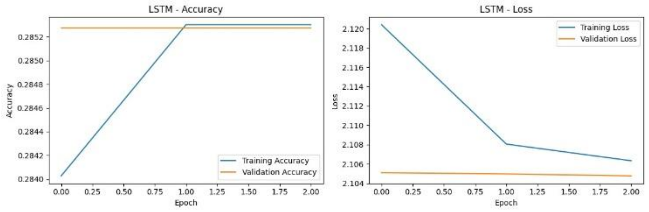
News Category Distribution (Huge Plot)



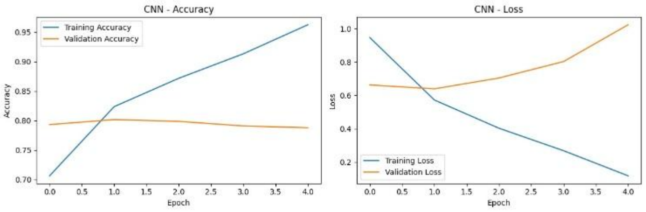
Model Loss – NN with TF-IDF



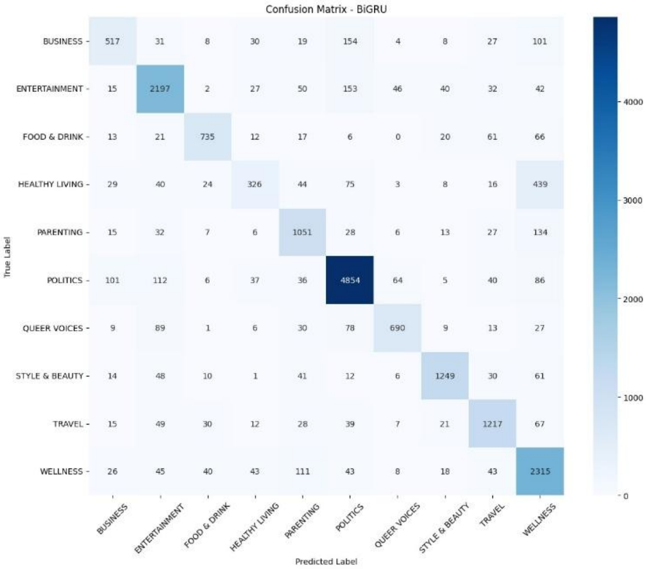
BiGRU Accuracy and Loss



LSTM Accuracy and Loss

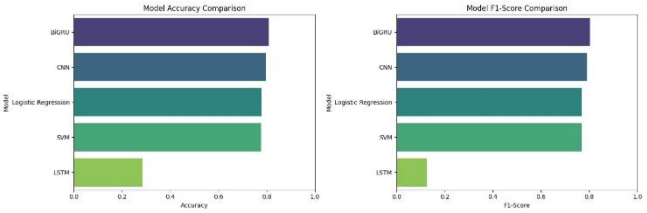


CNN Accuracy and Loss



| | BUSINESS | ENTERTAINMENT | FOOD & DRINK | HEALTHY LIVING | PARENTING | POLITICS | QUEER VOICES | STYLE & BEAUTY | TRAVEL | WELLNESS |
|---|---|---|---|---|---|---|---|---|---|---|
| BUSINESS | 517 | 31 | 8 | 30 | 19 | 154 | 4 | 8 | 27 | 101 |
| ENTERTAINMENT | 15 | 2197 | 2 | 27 | 50 | 153 | 46 | 40 | 32 | 42 |
| FOOD & DRINK | 13 | 21 | 735 | 12 | 17 | 6 | 0 | 20 | 61 | 66 |
| HEALTHY LIVING | 29 | 40 | 24 | 326 | 44 | 75 | 3 | 8 | 16 | 439 |
| PARENTING | 15 | 32 | 7 | 6 | 1051 | 28 | 6 | 13 | 27 | 134 |
| POLITICS | 101 | 112 | 6 | 37 | 36 | 4854 | 64 | 5 | 40 | 86 |
| QUEER VOICES | 9 | 89 | 1 | 6 | 30 | 78 | 690 | 9 | 13 | 27 |
| STYLE & BEAUTY | 14 | 48 | 10 | 1 | 41 | 12 | 6 | 1249 | 30 | 61 |
| TRAVEL | 15 | 49 | 30 | 12 | 28 | 39 | 7 | 21 | 1217 | 67 |
| WELLNESS | 26 | 45 | 40 | 43 | 111 | 43 | 8 | 18 | 43 | 2315 |

Confusion Matrix – BiGRU



Model Accuracy Comparison

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