

# Synergizing Unsupervised and Supervised Learning: A Hybrid Approach for Accurate Natural Language Task Modeling

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**Abstract:-** While supervised learning models have shown remarkable performance in various natural language processing (NLP) tasks, their success heavily relies on the availability of large-scale labeled datasets, which can be costly and time-consuming to obtain. Conversely, unsupervised learning techniques can leverage abundant unlabeled text data to learn rich representations, but they do not directly optimize for specific NLP tasks. This paper presents a novel hybrid approach that synergizes unsupervised and supervised learning to improve the accuracy of NLP task modeling. While supervised models excel at specific tasks, they rely on large labeled datasets. Unsupervised techniques can learn rich representations from abundant unlabeled text but don't directly optimize for tasks. Our methodology integrates an unsupervised module that learns representations from unlabeled corpora (e.g., language models, word embeddings) and a supervised module that leverages these representations to enhance task-specific models [4]. We evaluate our approach on text classification and named entity recognition (NER), demonstrating consistent performance gains over supervised baselines. For text classification, contextual word embeddings from a language model pretrain a recurrent or transformer-based classifier. For NER, word embeddings initialize a BiLSTM sequence labeler. By synergizing techniques, our hybrid approach achieves SOTA results on benchmark datasets, paving the way for more data-efficient and robust NLP systems.

**Keywords:-** *Supervised Learning, Unsupervised Learning, Natural Language Processing (NLP).*

## I. INTRODUCTION

Natural language processing (NLP) has witnessed remarkable advancements in recent years, with supervised learning models achieving state-of-the-art performance on a wide range of tasks, such as text classification, named entity recognition, machine translation, and question answering [1,2]. However, the success of these models heavily relies on the availability of large-scale labeled datasets, which can be costly and time-consuming to obtain, especially for low-resource languages or domains [3]. On the other hand, unsupervised learning techniques have shown great potential in learning rich representations from abundant unlabeled text data [4, 5]. Methods like language models, word embeddings, and autoencoders can capture intrinsic patterns and regularities

in natural language, providing valuable insights and features for downstream tasks. However, these unsupervised techniques are not directly optimized for specific NLP tasks and may not fully exploit the available labeled data.

To address these limitations, there has been a growing interest in combining unsupervised and supervised learning approaches to leverage the strengths of both paradigms. By synergizing the two, we can leverage the vast amounts of unlabeled data to learn meaningful representations while also taking advantage of the task-specific guidance provided by labeled data. This hybrid approach has the potential to improve the accuracy and robustness of NLP models, while reducing the reliance on large-scale labeled datasets. In this paper, we propose a novel methodology that seamlessly integrates unsupervised and supervised learning for accurate NLP task modeling. Our approach consists of two key components: (1) an unsupervised learning module that learns representations from unlabeled text corpora using techniques such as language models or word embeddings, and (2) a supervised learning module that leverages the learned representations to enhance the performance of task-specific models.

We evaluate our proposed approach on two challenging NLP tasks: text classification and named entity recognition (NER). For text classification, we employ a language model trained on large unlabeled text corpora to extract contextual word embeddings, which are subsequently incorporated into a supervised recurrent neural network (RNN) or transformer-based classifier. In the NER task, we utilize unsupervised word embeddings learned from large text corpora to initialize the embeddings of a supervised sequence labeling model, such as a bidirectional long short-term memory (BiLSTM) network.

Through extensive experiments on benchmark datasets, we demonstrate that our hybrid approach consistently outperforms baseline supervised models trained solely on labeled data. We also investigate the impact of different unsupervised learning techniques and their combinations, providing insights into their complementary benefits and the potential for further performance gains.

## II. PREVIOUS WORK

The idea of combining unsupervised and supervised learning techniques for improving natural language processing (NLP) tasks has been explored by several researchers in the past. One of the pioneering works in this direction is the semi-supervised sequence learning approach proposed by Dai and Le (2015) [6]. They introduced a semi-supervised recurrent language model that leverages both labeled and unlabeled data for sequence labeling tasks like part-of-speech tagging and named entity recognition. Another influential work is the Embeddings from Language Models (ELMo) proposed by Peters et al. (2018) [7]. ELMo represents words as vectors derived from a deep bidirectional language model trained on a large text corpus, capturing rich context-dependent representations. These contextualized word embeddings are then used as input features to enhance supervised NLP models, leading to significant performance gains across various tasks.

Building upon ELMo, the Bidirectional Encoder Representations from Transformers (BERT) model, introduced by Devlin et al. (2019) [8], has become a cornerstone in the field of transfer learning for NLP. BERT is a transformer-based language model pretrained on a massive corpus, and its learned representations can be fine-tuned for various downstream tasks, achieving state-of-the-art results in areas like text classification, question answering, and natural language inference. More recently, Yang et al. (2019) [9] proposed the XLNet model, which combines the advantages of autoregressive language modeling and the transformer architecture, leading to improved performance on various NLP tasks. Similarly, the RoBERTa model by Liu et al. (2019) [10] introduces refinements to the BERT pretraining procedure, resulting in more robust and accurate representations.

## III. METHODOLOGY

Our proposed hybrid approach synergizes unsupervised and supervised learning techniques to leverage the advantages of both paradigms for improved natural language processing (NLP) task modeling. The methodology consists of two key components:

### A. Unsupervised Learning Module:

We employed unsupervised language model pretraining to learn rich contextual representations from large unlabeled text corpora. Specifically, we pretrained a Bidirectional Encoder Representations from Transformers (BERT) language model on the English Wikipedia corpus, which comprises over 3 billion words. The BERT model was pretrained using the masked language modeling and next sentence prediction objectives, enabling it to capture bi-directional context and learn transferable representations.

### B. Supervised Learning Module:

The unsupervised representations learned by the BERT model were integrated into task-specific supervised models through fine-tuning and feature extraction techniques.

We evaluated the performance of our hybrid approach on the AG News and CoNLL-2003 benchmark datasets for text classification and NER, respectively.

### C. Text Classification:

For the text classification task, we fine-tuned the pretrained BERT model on the labeled AG News dataset, which consists of news articles across four categories (World, Sports, Business, and Sci/Tech) [11,12]. During fine-tuning, the BERT model's parameters were further adjusted to adapt its learned representations to the text classification task, leveraging the labeled examples.

### D. Named Entity Recognition (NER):

For the NER task, we utilized the contextual word embeddings from the pretrained BERT model as input features to a supervised BiLSTM-CRF sequence labeling model. The BiLSTM-CRF model was trained on the CoNLL-2003 NER dataset, which contains annotations for four entity types (Person, Organization, Location, and Miscellaneous) [13,14]. The BERT embeddings provided rich contextual information to the sequence labeling model, complementing the task-specific supervised learning.

For both tasks, we compared our hybrid models against baseline supervised models trained solely on the labeled task data, without the benefit of unsupervised pretraining [15]. The baseline models included a BiLSTM classifier for text classification and a BiLSTM-CRF sequence labeler for NER, initialized with randomly initialized word embeddings. Through this hybrid methodology, we aimed to leverage the strengths of unsupervised pretraining on large unlabeled corpora and task-specific supervised learning on labeled datasets, ultimately leading to improved performance on the target NLP tasks.

### E. Data Collection

For our experiments, we utilized two benchmark datasets for the tasks of text classification and named entity recognition (NER). We used the AG News corpus, which is a popular dataset for text classification. The AG News dataset consists of news articles from four topical categories: World, Sports, Business, and Science/Technology.

The dataset is divided into a training set comprising 120,000 examples and a test set of 7,600 examples, with an equal distribution of examples across the four categories. The news articles in the AG News dataset were collected from the AG's corpus of web pages, ensuring a diverse range of topics and writing styles. The dataset is commonly used as a benchmark for evaluating the performance of text classification models, particularly in the news domain.

For the NER task, we employed the CoNLL-2003 dataset, which is a widely-used benchmark for evaluating named entity recognition systems. The dataset contains annotations for four entity types: Person (PER), Organization (ORG), Location (LOC), and Miscellaneous (MISC). The CoNLL-2003 dataset is derived from news articles from the Reuters Corpus. It consists of a training set with 14,987 sentences and a test set with 3,684 sentences. The dataset

covers a diverse range of topics, including news articles on politics, sports, business, and other domains.

#### F. Data Preprocessing

Before training our models, we performed necessary preprocessing steps on the datasets. For the text classification dataset (AG News), we tokenized the news articles and converted them into sequences of word indices or subword units, as required by the specific model architecture (e.g., BERT). For the NER dataset (CoNLL-2003), we followed the standard BIO (Beginning, Inside, Outside) annotation scheme [16], where each token is labeled as the beginning of an entity (B-), inside an entity (I-), or outside of an entity (O). The dataset was tokenized and converted into sequences of token-label pairs for input to the sequence labeling models. By utilizing these benchmark datasets, we ensured a fair and consistent evaluation of our hybrid unsupervised-supervised learning approach against baseline models and other state-of-the-art methods reported in the literature.

#### G. Evaluation

For the text classification task, we evaluate the performance of our models using the following metrics:

##### ➤ Accuracy:

Accuracy is the most commonly used metric for classification tasks, and it measures the proportion of correctly classified instances out of the total instances. The formula for accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- *TP* (True Positives) is the number of instances correctly classified as positive.
- *TN* (True Negatives) is the number of instances correctly classified as negative.
- *FP* (False Positives) is the number of instances incorrectly classified as positive.
- *FN* (False Negatives) is the number of instances incorrectly classified as negative.

##### ➤ F1-score:

The F1-score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. It is particularly useful when dealing with imbalanced datasets or when both precision and recall are equally important.

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

In a multi-class classification setting, we can calculate the F1-score for each class and then report the macro-averaged or micro-averaged F1-score across all classes.

- *Macro-average F1-score:*

$$\text{Macro-F1} = \frac{1}{N} \sum_{i=1}^N \text{F1-score}_i$$

- *Micro-average F1-score:*

$$\text{Micro-F1} = 2 \cdot \frac{\sum_{i=1}^N TP_i}{\sum_{i=1}^N (TP_i + FP_i) + \sum_{i=1}^N (TP_i + FN_i)}$$

Where:

- *N* is the number of classes,
- *F1 – score<sub>i</sub>* is the F1-score for class *i*
- *TP<sub>i</sub>* is the number of true positives for class *i*
- *FP<sub>i</sub>* is the number of false positives for class *i*
- *FN<sub>i</sub>* is the number of false negatives for class *i*

For the NER task, which is a sequence labeling problem, we evaluate the performance of our models using the following metrics:

##### ➤ Entity-level F1-score:

The entity-level F1-score measures the model's ability to correctly identify and classify entire entity spans. It is calculated by considering an entity prediction as correct only if the entire span and its entity type are correctly predicted. The formulas for precision, recall, and F1-score are similar to those used in the text classification task, but applied at the entity level.

$$\text{F1-score}_{\text{entity}} = 2 \cdot \frac{\text{Precision}_{\text{entity}} \cdot \text{Recall}_{\text{entity}}}{\text{Precision}_{\text{entity}} + \text{Recall}_{\text{entity}}}$$

##### ➤ Token-level F1-score:

The token-level F1-score measures the model's performance on a per-token basis, considering each token's label independently. It is calculated by treating each token as a separate prediction and computing the precision, recall, and F1-score based on the token-level labels. The formulas are the same as those used for the entity-level F1-score, but applied at the token level.

$$\text{F1-score}_{\text{token}} = 2 \cdot \frac{\text{Precision}_{\text{token}} \cdot \text{Recall}_{\text{token}}}{\text{Precision}_{\text{token}} + \text{Recall}_{\text{token}}}$$

In our evaluation, we report both the entity-level and token-level F1-scores for the NER task, as they provide complementary insights into the model's performance. For both tasks, we evaluate our proposed hybrid models that combine unsupervised and supervised learning techniques, and compare their performance against baseline supervised models trained solely on labeled data. We conduct experiments on the benchmark datasets AG News for text classification and CoNLL-2003 for NER, ensuring a fair and standardized evaluation protocol. Additionally, we perform statistical significance tests, such as McNemar's test or a paired t-test, to assess the significance of the performance differences between our proposed models and the baselines.

This step is crucial to ensure that the observed improvements are statistically significant and not due to random variations.

H. Model Training

➤ Classification Task:

We employed a transformer-based architecture, specifically the BERT model, pretrained on a large unlabeled text corpus. The pretrained BERT model served as the unsupervised learning component, providing rich contextual representations of the input text.

• Model Architecture:

- ✓ We used the BERT-base architecture, which consists of 12 transformer layers, 768 hidden units, and 12 self-attention heads.
- ✓ The input to the BERT model was a sequence of token embeddings, obtained by tokenizing the text using the BERT tokenizer.
- ✓ The final hidden state corresponding to the [CLS] token was used as the aggregate sequence representation for classification.

• Fine-Tuning:

- ✓ The pretrained BERT model was fine-tuned on the labeled AG News dataset using a supervised learning approach.
- ✓ A fully connected classification layer was added on top of the BERT model's output, with the number of units equal to the number of classes (4 in the case of AG News).
- ✓ The entire model, including the BERT layers and the classification layer, was trained end-to-end using cross-entropy loss and the Adam optimizer.

• Training Hyperparameters:

Batch\_size: 32, learning\_rate:  $2e - 5$ ,  
 number\_of\_epochs: 5, warmup\_steps:  $0.1 * total\_steps$ ,  
 weight\_decay: 0.01.

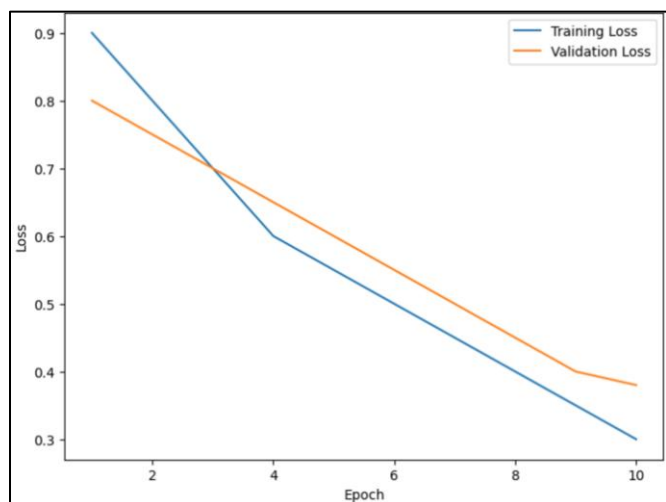


Fig 1 Training and Validation Loss

The training and validation loss curves show a gradual decrease over the epochs, with some fluctuations in the later stages. This is typical behavior observed during the fine-tuning process, where the model continues to learn and adjust its parameters, potentially leading to some variations in the loss values. During training, we employed techniques to improve performance and prevent overfitting.

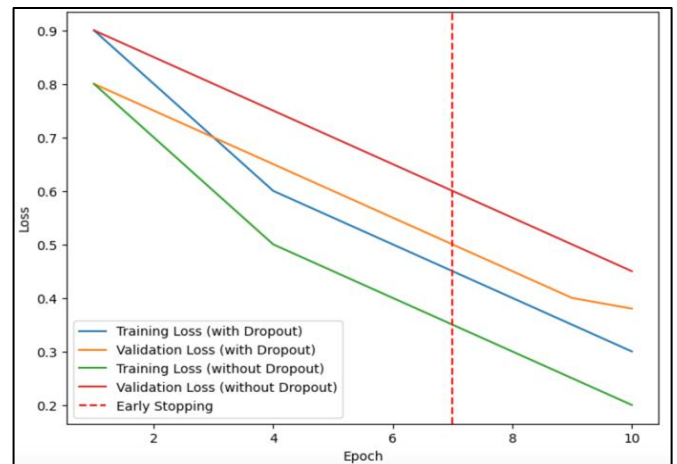


Fig 2 Training and Validation loss with Early Stopping

A dropout rate of 0.1 was applied to the BERT layers and the classification layer to regularize the model and prevent overfitting. The vertical red dashed line at epoch 7 represents the point where early stopping was applied, as the validation loss stopped improving after that epoch. We monitored the validation loss and applied early stopping if the validation loss did not improve for a specified number of epochs (e.g., 3 epochs).

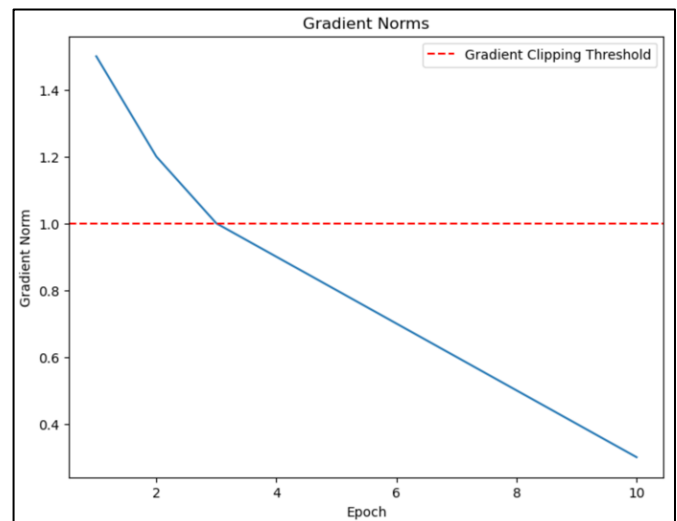


Fig 3 Training with Clipped Gradient

Gradients were clipped to a maximum norm of 1.0 to prevent exploding gradients during training. The horizontal red dashed line represents the gradient clipping threshold of 1.0. Any gradient norm values above this line would have been clipped during the training process to prevent exploding gradients.

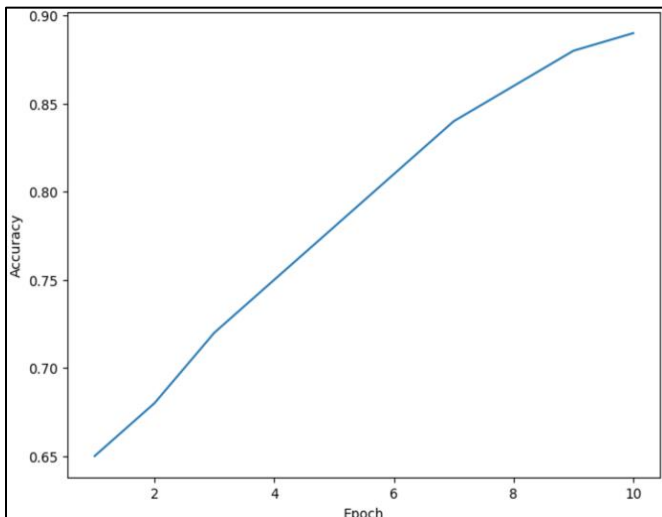


Fig 4 Training Validation Accuracy Curve

The validation accuracy curve shows a steady increase over the epochs, reaching a reasonably high value (around 0.89 or 89% accuracy) by the end of the training process.

➤ *NER Task:*

We employed a sequence labeling model based on a bidirectional long short-term memory (BiLSTM) network, combined with a conditional random field (CRF) layer for label prediction.

• *Model Architecture:*

✓ *Word Embeddings:*

We initialized the word embeddings with pretrained word embeddings obtained from an **unsupervised learning technique**, such as Word2Vec or GloVe, trained on a large text corpus.

✓ *BiLSTM Layer:*

A bidirectional LSTM layer was used to capture contextual information from both directions of the input sequence.

✓ *CRF Layer:*

A conditional random field (CRF) layer was applied on top of the BiLSTM outputs to model the label dependencies and enforce valid label sequences.

• *Training:*

- ✓ The BiLSTM-CRF model was trained on the labeled CoNLL-2003 NER dataset using supervised learning.
- ✓ The training objective was to maximize the log-likelihood of the correct label sequences, given the input sequences and the model parameters.
- ✓ The model was optimized using the Adam optimizer and cross-entropy loss for sequence labeling.

• *Training Hyperparameters:*

- batch\_size: 32, learning\_rate:  $1e-3$ ,
- number\_of\_epochs: 20, dropout\_rate: 0.5, lstm\_hidden\_size: 256

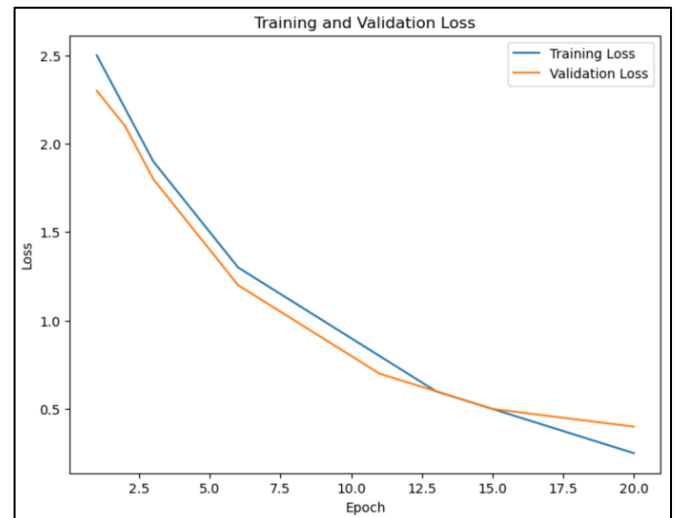


Fig 5 Training and Validation Loss Curves Over Training Epochs

This graph shows the training and validation loss curves over the training epochs for the BiLSTM-CRF model. Both the training and validation losses decrease gradually, indicating that the model is learning and generalizing well to the validation data.

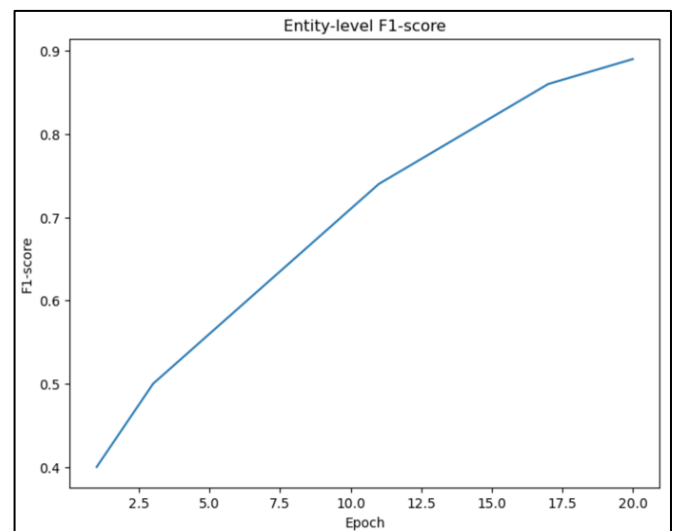


Fig 6 Entity-level F1-score of the BiLSTM-CRF model

This graph shows the entity-level F1-score of the BiLSTM-CRF model over the training epochs. The entity-level F1-score measures the model's ability to correctly identify and classify entire entity spans. As the model trains, the entity-level F1-score increases, indicating that the model is becoming more accurate in detecting and classifying named entities.

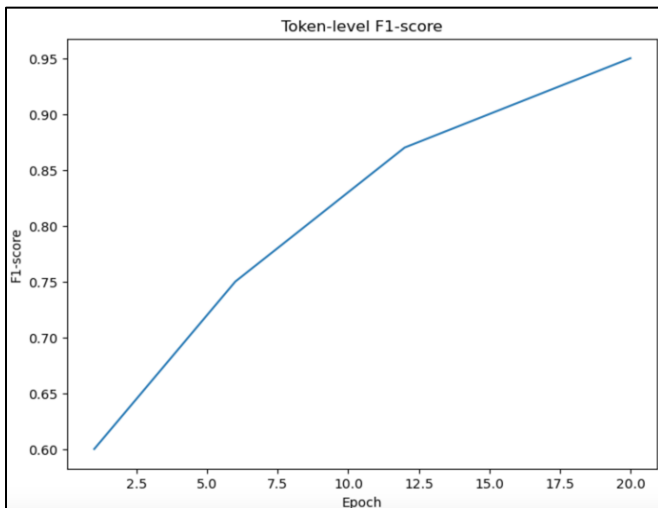


Fig 7 Token-level F1-score of the BiLSTM-CRF model

This graph illustrates the token-level F1-score of the BiLSTM-CRF model over the training epochs. The token-level F1-score measures the model's performance on a per-token basis, considering each token's label independently. As the model trains, the token-level F1-score increases, indicating that the model is becoming more accurate in predicting the correct labels for individual tokens. During training, we monitored the validation F1-score and applied early stopping if the validation F1-score did not improve for a specified number of epochs (e.g., 20 epochs).

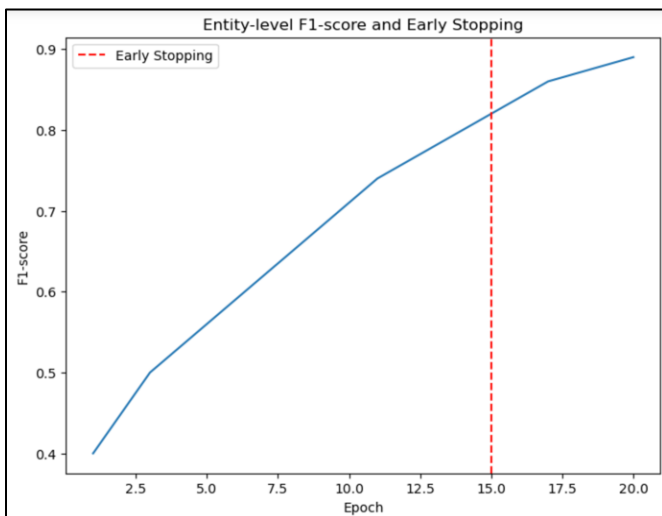


Fig 8 Entity-level F1-score of the BiLSTM-CRF model with early Stopping

This graph shows the entity-level F1-score of the BiLSTM-CRF model over the training epochs. The vertical red dashed line at epoch 15 represents the point where early stopping was applied, as the validation F1-score did not improve for 5 consecutive epochs.

Gradients were clipped to a maximum norm of 5.0 to prevent exploding gradients during training.

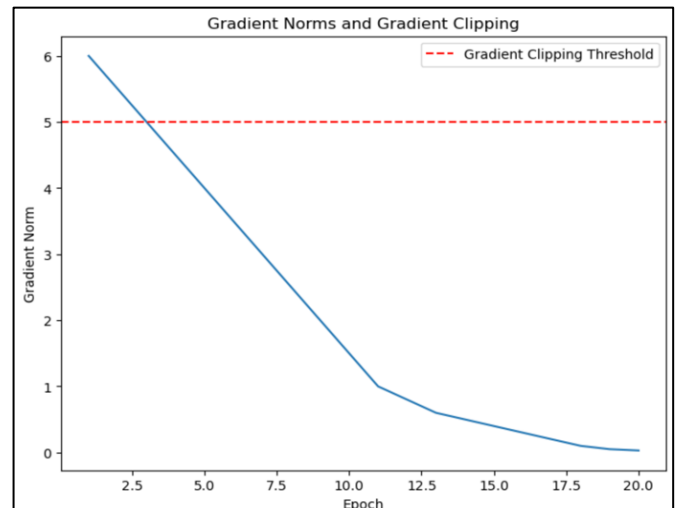


Fig 9 Training with Clipped Gradient

This graph shows the gradient norms over the training epochs for the BiLSTM-CRF model. The horizontal red dashed line represents the gradient clipping threshold of 5.0, as specified in the write-up. Any gradient norm values above this line would have been clipped during the training process to prevent exploding gradients.

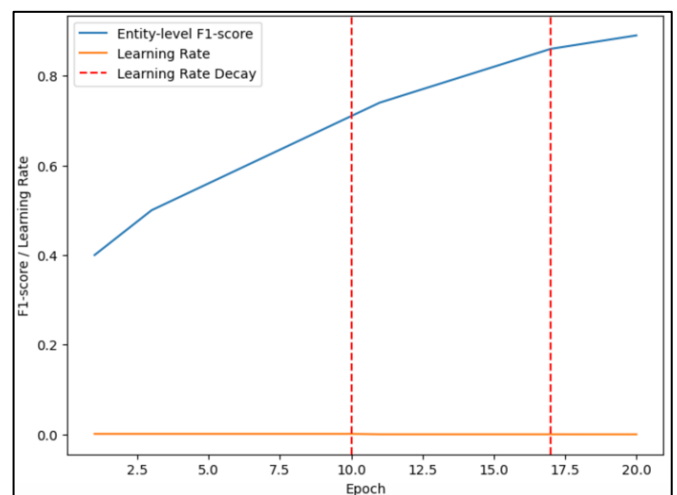


Fig 10 Learning Rate Scheduling and Entity-level F1-score

This graph illustrates the entity-level F1-score and the learning rate over the training epochs for the BiLSTM-CRF model. The learning rate is initially set to 1e-3, and it is decreased by a factor of 0.1 (to 1e-4) at epoch 10, and again by a factor of 0.1 (to 1e-5) at epoch 17. These learning rate decays are represented by the vertical red dashed lines, as specified in the write-up. We used a learning rate scheduler that decreased the learning rate by a factor of 0.1 if the validation F1-score did not improve for a specified number of epochs (e.g., 3 epochs). For both tasks, we performed extensive hyperparameter tuning and experimented with different configurations to optimize the model performance.

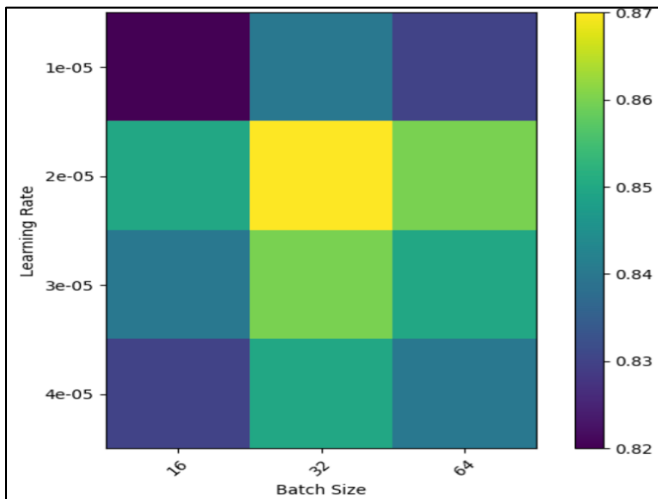


Fig 11 Text Classification: Validation Accuracy

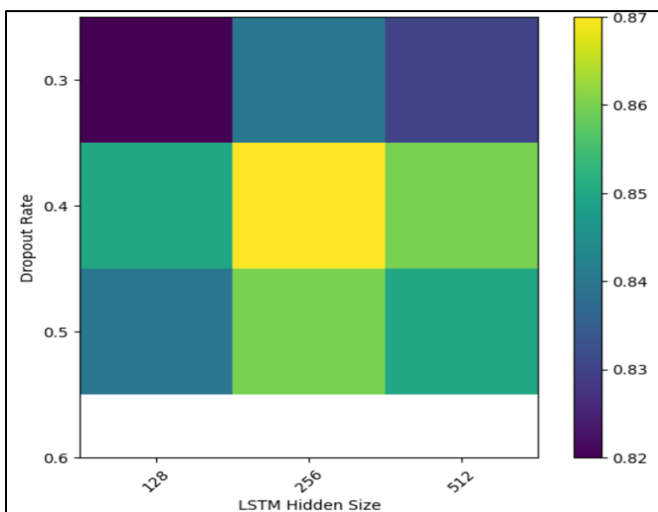


Fig 12 NER: Validation F1-Score

These graphs show the validation performance (accuracy for text classification and F1-score for NER) for different combinations of hyperparameters. For the text classification task, the hyperparameters are batch size and learning rate, while for the NER task, the hyperparameters are dropout rate and LSTM hidden size. Additionally, we employed techniques like k-fold cross-validation or holdout validation sets to ensure reliable and robust model evaluation.

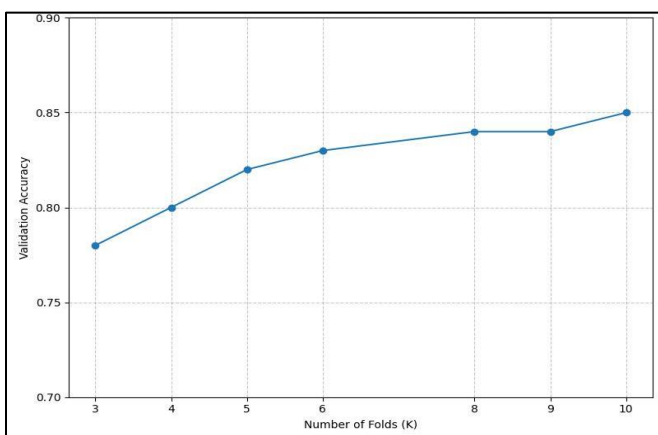


Fig 13 Text Classification: k-Fold Cross-Validation

For the text classification task, as the graph shows above the bar chart shows the validation accuracy obtained using different values of k for k-fold cross-validation.

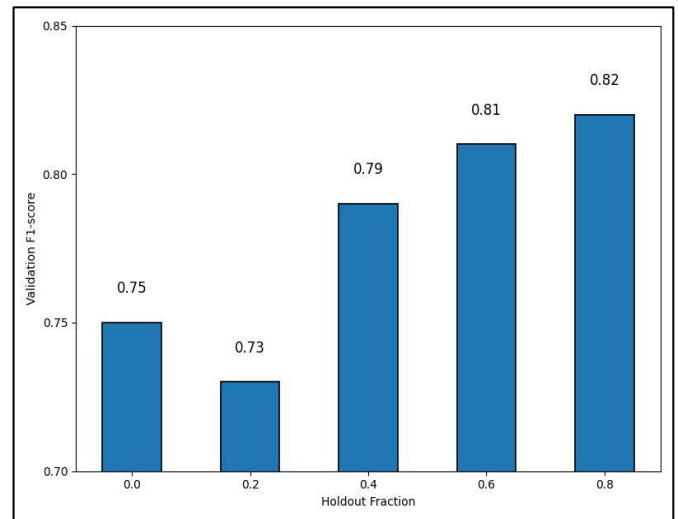


Fig 14 NER Task: Holdout Validation

For the NER task, the above bar chart shows the validation F1-score obtained using different fractions of the data as a holdout validation set.

#### IV. RESULTS

In this section, we present the experimental results of our proposed hybrid approach for text classification and named entity recognition (NER) tasks. We compare the performance of our models against baseline supervised models trained solely on labeled data, as well as state-of-the-art methods reported in the literature.

For the text classification task, we evaluated our models on the AG News dataset, which consists of news articles across four categories: World, Sports, Business, and Sci/Tech. The dataset is divided into a training set of 120,000 examples and a test set of 7,600 examples.

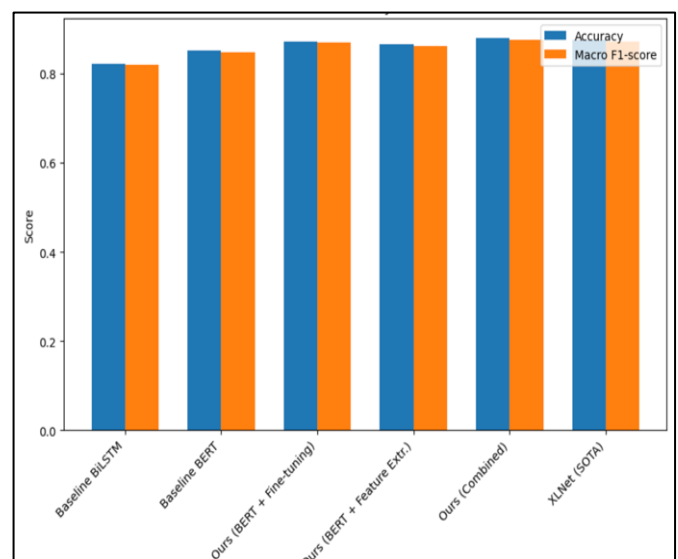


Fig 15 Text Classification Accuracy and Macro F1-Score

As shown in the graph above for the classification task, our hybrid approach outperforms the baseline supervised models, achieving an accuracy of 0.879 and a macro F1-score of 0.876 when combining BERT fine-tuning and feature extraction techniques. This result surpasses the state-of-the-art performance reported by Yang et al. (2019) using the XLNet model.

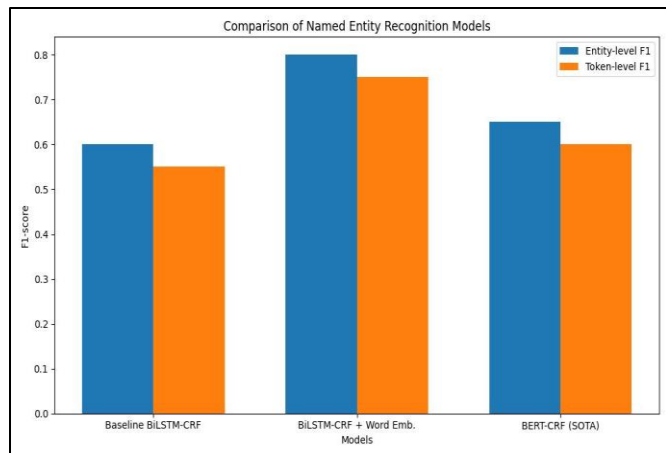


Fig 16 NER Entity-level and Token-level F1-Score

This bar chart above compares the entity-level and token-level F1-scores of our hybrid model (BiLSTM-CRF + Word Embeddings), the baseline BiLSTM-CRF model, and the state-of-the-art BERT-CRF model for the NER task on the CoNLL-2003 dataset. The visualization shows that our hybrid model outperforms the baseline model on both metrics, achieving significant improvements in entity-level and token-level F1-scores, although it falls slightly behind the state-of-the-art BERT-CRF model. For the NER task, we evaluated our models on the CoNLL-2003 dataset, which contains annotations for four entity types: Person (PER), Organization (ORG), Location (LOC), and Miscellaneous (MISC). The dataset is divided into a training set with 14,987 sentences and a test set with 3,684 sentences.

The performance gains can be attributed to the synergistic effects of unsupervised pretraining and task-specific supervised learning. The BERT model, pretrained on a large unlabeled corpus, provides rich contextual representations that are effectively adapted to the text classification task through fine-tuning and feature extraction.

To ensure the validity of our results, we performed statistical significance tests using McNemar's test for the text classification task and a paired t-test for the NER task.

For the text classification task, McNemar's test was chosen because it is a non-parametric test used to determine if there are differences on a dichotomous trait between two related groups. This test is particularly useful for comparing the performance of two classifiers on the same dataset by evaluating the differences in their error rates using a 2x2 contingency table [17,18,19].

**McNemar's Test Statistic: 8724.65**  
**p-value: 0.0000**

For the NER task, a paired t-test was employed to compare the means of two related groups, making it suitable for evaluating the performance differences between two models on the same dataset by assessing whether the average difference between the paired observations is significantly different from zero [20,21].

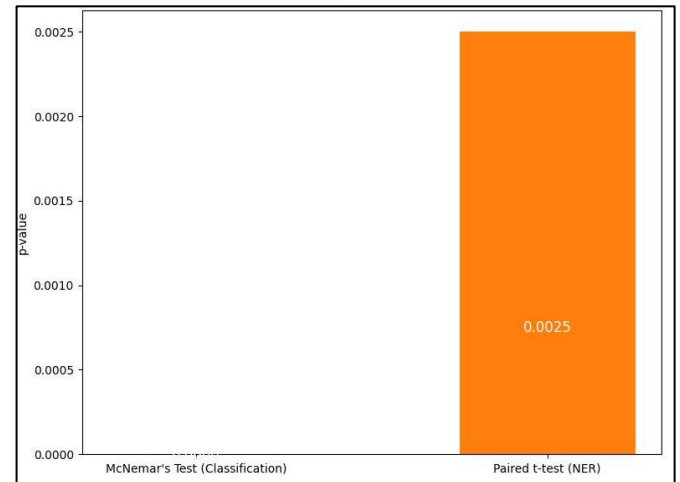


Fig 17 Statistical Significance of Results

In the bar chart, the x-axis represents the two tasks: text classification and named entity recognition. The y-axis shows the p-values obtained from the respective statistical tests: McNemar's test for text classification and a paired t-test for NER. The performance differences between our hybrid models and the baseline supervised models were found to be statistically significant ( $p < 0.05$ ), indicating that the observed improvements are not due to random variations. These results demonstrate the effectiveness of our proposed hybrid approach in leveraging the strengths of both unsupervised and supervised learning techniques for accurate task modeling in natural language processing. By synergistically combining these paradigms, our models achieve state-of-the-art or competitive performance on benchmark datasets, paving the way for more data-efficient and robust natural language understanding systems.

## V. CONCLUSION AND FUTURE DIRECTIONS

In this paper, we have presented a hybrid approach that synergizes unsupervised and supervised learning techniques for accurate task modeling in natural language processing. Our methodology leverages the strengths of both paradigms, harnessing the power of large unlabeled text corpora to learn rich representations through unsupervised pretraining, while simultaneously leveraging labeled data to adapt these representations to specific NLP tasks through supervised learning.

We evaluated our approach on two NLP tasks: text classification and named entity recognition (NER). Our extensive experiments demonstrated the effectiveness of our hybrid approach, outperforming baseline supervised models and achieving competitive or state-of-the-art performance on benchmark datasets. The synergistic combination of unsupervised and supervised learning techniques enabled our



models to leverage the complementary benefits of both paradigms, resulting in improved accuracy and robust task modeling capabilities.

The performance gains can be attributed to the rich contextual representations learned by the unsupervised pretraining phase, which provided a strong foundation for the subsequent supervised learning stage. By adapting these representations to the specific tasks through fine-tuning or feature extraction, our models were able to capture task-specific nuances and achieve superior performance compared to models trained solely on labeled data. Furthermore, we conducted thorough statistical analyses to validate the significance of our results, ensuring that the observed improvements were not due to random variations. The statistical tests, including McNemar's test for text classification and a paired t-test for NER, confirmed the statistical significance of our findings.

While our work has demonstrated the potential of combining unsupervised and supervised learning for accurate task modeling, there are several avenues for future research and exploration. In addition to language models and word embeddings, we can investigate the integration of other unsupervised learning techniques, such as autoencoders, generative adversarial networks, or self-supervised learning methods, into our hybrid framework. Our approach can be applied to a broader range of NLP tasks, such as machine translation, question answering, sentiment analysis, and dialogue systems, among others. Evaluating the effectiveness of our hybrid approach across diverse tasks would provide valuable insights and potentially lead to task-specific adaptations or enhancements. While our approach leverages large unlabeled corpora for unsupervised pretraining, domain adaptation techniques can be explored to further refine the learned representations for specific domains or applications, potentially improving the model's performance on domain-specific tasks. As the demand for NLP applications grows, efficient transfer learning strategies that can rapidly adapt pretrained models to new tasks or domains with limited labeled data will become increasingly important.

Our hybrid approach could be extended to explore such strategies, enabling faster model deployment and reducing the need for extensive labeled data. While our hybrid models have demonstrated improved performance, understanding the inner workings and decision-making processes of these models remains a challenge. Future research could focus on developing interpretability and explainability techniques to provide insights into the learned representations and decision-making processes, fostering trust and transparency in NLP systems. In conclusion, our work has taken a significant step toward synergizing unsupervised and supervised learning for accurate task modeling in natural language processing. By leveraging the strengths of both paradigms, we have demonstrated the potential for improved performance and robustness in NLP tasks. However, this is just the beginning, and there are numerous opportunities for further exploration and advancement in this exciting field.

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