INFO-H519 - NLP with Deep Learning - SP24

# Fine Tuning BERT on Sentimental Analysis

**BERT | LLM**

**Professor Ming Jiang**

**Group1**
Hasaranga Jayathilake
Hari Shivani Gudi
Hymavathi Gummudala

LUDDY
SCHOOL OF INFORMATICS, COMPUTING, AND ENGINEERING
INDIANAPOLIS

# Lineup

- Introduction
- Prior Related Work (Literature Review)
- Data
- Approach
- Experiments
- Results
- Analysis & Conclusion

SECTION 1

# Introduction

# Background

- **Feedback** and **reviews** are important for the organizations to be relevant on the current market trends and achieve sustainable competitive advantage.

- **Sentiment analysis** using NLP is crucial for **leveraging feedback data effectively** and conduct market research in present of Big Data market.

- Predominately, Sentiment Analysis involves **classifying text** based on the sentiment or opinion expressed (**positive**, **negative**, or **neutral**).

- Developing sentiment analysis models for **multiple languages** allows us to better understand and engage with a **global audience**.

# Languages Focused


**Vietnamese** is spoken as first language by **approximately 86 million people** and features a complex phonetic and grammatical structure.

- There is less availability of pre-trained models and linguistic resources compared to English.
- **There is an emerging interest in NLP research and application for Vietnamese.**

**English** is spoken as first language by around **1.45 billion people** and is the dominant language in trade, research and technology.

- Extensive pre-trained models and resources are available.
- Well-established best practices and techniques for sentiment analysis.

# Most Spoken Languages on Earth, 2023

Top 40 most spoken language in the world, based on the highest number of speakers

| | | | | | |
|---|---|---|---|---|---|
| 1 | English | 1.456 B | 21 | Vietnamese | 86 M |
| 2 | Mandarin Chinese | 1.138 B | 22 | Wu Chinese | 83 M |
| 3 | Hindi | 610 M | 23 | Tagalog | 83 M |
| 4 | Spanish | 559 M | 24 | Korean | 82 M |
| 5 | French | 310 M | 25 | Iranian Persian | 79 M |
| 6 | Standard Arabic | 274 M | 26 | Hausa | 79 M |
| 7 | Bengali | 273 M | 27 | Swahili | 72 M |
| 8 | Portuguese | 264 M | 28 | Javanese | 68 M |
| 9 | Russian | 255 M | 29 | Italian | 68 M |
| 10 | Urdu | 232 M | 30 | Western Punjabi | 67 M |
| 11 | Indonesian | 199 M | 31 | Gujarati | 62 M |
| 12 | Standard German | 133 M | 32 | Thai | 61 M |
| 13 | Japanese | 123 M | 33 | Kannada | 59 M |
| 14 | Nigerian Pidgin | 121 M | 34 | Amharic | 58 M |
| 15 | Egyptian Arabic | 102 M | 35 | Bhojpuri | 52 M |
| 16 | Marathi | 99 M | 36 | Eastern Punjabi | 52 M |
| 17 | Telugu | 96 M | 37 | Min Nan Chinese | 50 M |
| 18 | Turkish | 90 M | 38 | Jin Chinese | 48 M |
| 19 | Tamil | 87 M | 39 | Levantine Arabic | 48 M |
| 20 | Yue Chinese | 87 M | 40 | Yoruba | 46 M |

*Source: Ethnologue, 2023*

| Country | Region | Official language | Distribution | Total |
|---|---|---|---|---|
| Vietnam | Southeast Asia | yes | 86.8 % | 85,226,000 |
| Cambodia | Southeast Asia | no | 5.5 % | 922,000 |
| United States of America | North America | no | 0.2 % | 667,000 |
| Australia | Australia/New Zealand | no | 1.1 % | 286,000 |

# Objectives

- Evaluate Sentiment detection accuracy on the current available models on Vietnamese Language

| Model Name | Developer | GitHub Link |
|---|---|---|
| BERT-Base, Multilingual Cased | Google (Devlin et al. in 2018) | Link |
| Fine-Tune BERT-Base, Multilingual Cased | Nguyen, et al., 2020 | Link |
| PhoBERT Model | Nguyen, et al., 2020 | Link |

- Fine-Tune by combining current models with other model architectures.

| Model Name | New Mode Integrations |
|---|---|
| BERT-Base, Multilingual Cased | + LSTM, +FastText, + Glove |
| Fine-Tune BERT-Base, Multilingual Cased | + LSTM, +FastText, + Glove |
| PhoBERT Model | + LSTM, +FastText, + Glove |

- Evaluate and Compare the model performances on English language dataset

| Dataset Name | Link |
|---|---|
| Vietnamese Hotel Reviews (NTC-SV) | Link |
| English IMDB Movie Reviews | Link |

| Evaluation Parameters |
|---|
| Accuracy (%) |
| Precision (%) |
| Recall (%) |
| F1 (%) |

- Provide insights into the challenges and opportunities of conducting sentiment analysis across multiple languages.

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- **Provide insights into the challenges and opportunities of conducting sentiment analysis across multiple languages.**

Section 2

# Prior Related Work

Literature Review

# Literature Review

**Focusing on sentiment analysis and the fine-tuning of BERT models**

## Development of BERT and Its Impact

- Jacob et al. (2018) BERT revolutionized NLP by understanding context in text efficiently.
- BERT's introduction changed how models process language, improving understanding across various NLP applications (Dang et al,. 2022).

| Research Paper Name and Reference | Methods Used |
|---|---|
| Multi-task solution for aspect category sentiment analysis on Vietnamese datasets (Dang et al,. 2022). | Transfer learning on BERT model |

## Multilingual and Cross-Lingual Challenges

- BERT adaptations handle multiple languages, aiding sentiment analysis where resources for languages like Vietnamese lag (Lê et al,. 2020).
- Multilingual BERT overcomes resource gaps in languages, enhancing sentiment analysis across diverse linguistic landscapes (Lê et al,. 2020).

| Research Paper Name and Reference | Methods Used |
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| On Vietnamese sentiment analysis: A transfer learning method. (Lê et al,. 2020). | Multilingual pre-trained language BERT model |

## Integration of BERT with Other Models

- Integrating BERT with LSTM improves sentiment analysis by enhancing text classification capabilities significantly (Luc, et al, 2021).
- Studies show BERT, combined with deep learning models like CNNs, elevates performance in text analysis. (Luc, et al, 2021).

| Research Paper Name and Reference | Methods Used |
|---|---|
| From aspect-based sentiment analysis to social listening system for business intelligence. (Luc, et al, 2021). | Ensemble deep learning architecture CNN and Bi-LSTM models |

## Effectiveness of Fine-Tuning on Domain-Specific Datasets

- Fine-tuning BERT on domain-specific datasets significantly boosts performance by aligning model focus with contextual nuances (Thin, et al,. 2020).
- Howard et al. demonstrated that domain-specific fine-tuning of BERT enhances model accuracy and relevance (Thin, et al,. 2020).

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# Limitations and Gaps in Existing Research

### Lack of comparison across models specialized for Vietnamese language (e.g., PhoBERT)

- Limited direct comparisons of Vietnamese-specific models (e.g. PhoBERT) hinder understanding of their effectiveness.
- Few studies analyze how different models handle Vietnamese language nuances.

### Limited evaluation of model effectiveness for Vietnamese language analysis

- Lack of broad assessment across a range of metrics for Vietnamese datasets.
- Insufficient analysis of model performance in different domains.

### Lack comparison with other languages like English to measure generalizability

- Limited comparisons with other languages (e.g., English) restrict the measurement of model generalizability.
- Lack of cross-language insights hampers understanding of model adaptability and robustness.

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# Project Focus: (Novelty of the Project)

| Task | Task definition | Input[1] | Outcome[2] |
|---|---|---|---|
| $\text{BERT}_{\text{BASE}}$ Vs PhoBERT | PhoBERT Model output metrics check against the BERT-Base-Multilingual Cased model output based on dataset used in original article. | Vietnam Hotel Food Review Dataset with Vietnam positive and negative word corpus | Generate prediction of either 0 (negative) or 1 (positive) for each text and their respective evaluation of Accuracy, Precision, Recall and F1 metrics. |
| $\text{BERT}_{\text{BASE}}$ on IMDB Data | $\text{BERT}_{\text{BASE}}$, FastText and Glove models separately embedding with the classification models such as LSTM, TextCNN and RCNN evaluate on the English dataset to compare the differences with original accuracies in terms of language performance.[3] | IMDB Dataset with English positive and negative word corpus | |

Section 3

# Data

# Datasets

## IMDB Dataset

| Dataset Analogy |
|---|
| Movie Review descriptions |
| 50000 Rows of Text Data |
| Sentiment defined using 2 Labels |
| Label: 0 - Negative |
| Label: 1 - Positive |

```
                                                    text  label
0      Forget what I said about Emeril. Rachael Ray i...      0
1      Former private eye-turned-security guard ditch...      0
2      Mann photographs the Alberta Rocky Mountains i...      0
3      Simply put: the movie is boring. Cliché upon c...      0
4      Now being a fan of sci fi, the trailer for thi...      1
...                                                  ...    ...
49995  The "documentary", and we use that term loosel...      0
49996  This outlandish Troma movie is actually a very...      1
49997  I found the film Don't Look In The Basement to...      1
49998  I have read the novel Reaper of Ben Mezrich a ...      0
49999  Went to see this finnish film and I've got to ...      1

[50000 rows x 2 columns]
```

## Vietnamese Dataset

| Dataset Analogy | |
|---|---|
| Pre-existing split dataset with train and test sub-datasets | |
| Hotel Food Review Descriptions | |
| Train Dataset | Test Dataset |
| 40761 Rows Data | 10000 Rows Data |
| Sentiment defined using 2 Labels | |
| Label: 0 - Negative | |
| Label: 1 - Positive | |

| | text | label |
|---|---|---|
| 0 | đồ_ăn ngon positive hợp_khẩu vị nhiều món nhân... | 0 |
| 1 | chè bơ thơm positive có vị ngậy ngậy nhưng lại... | 0 |
| 2 | chiều hôm nay mới đi ăn về nghe thiên_hạ đồn q... | 0 |
| 3 | mình đặt_hàng qua tin nhắn với cửa_hàng hứa sá... | 0 |
| 4 | ghé mấy lần rồi mà không review đi đâu cũng ch... | 1 |

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# Data Distribution across Different Labels

| Dataset | Train | | Test | |
|---|---|---|---|---|
| | Positive | Negative | Positive | Negative |
| IMDB | 19961 | 20039 | 5039 | 4961 |
| Vietnamese | 20493 | 20268 | 5000 | 5000 |

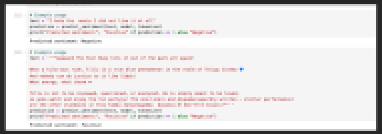
Section 4

# Approach

# Fine Tuning

Approach

Predict the sentiment label using example usage



Train & Evaluating Model

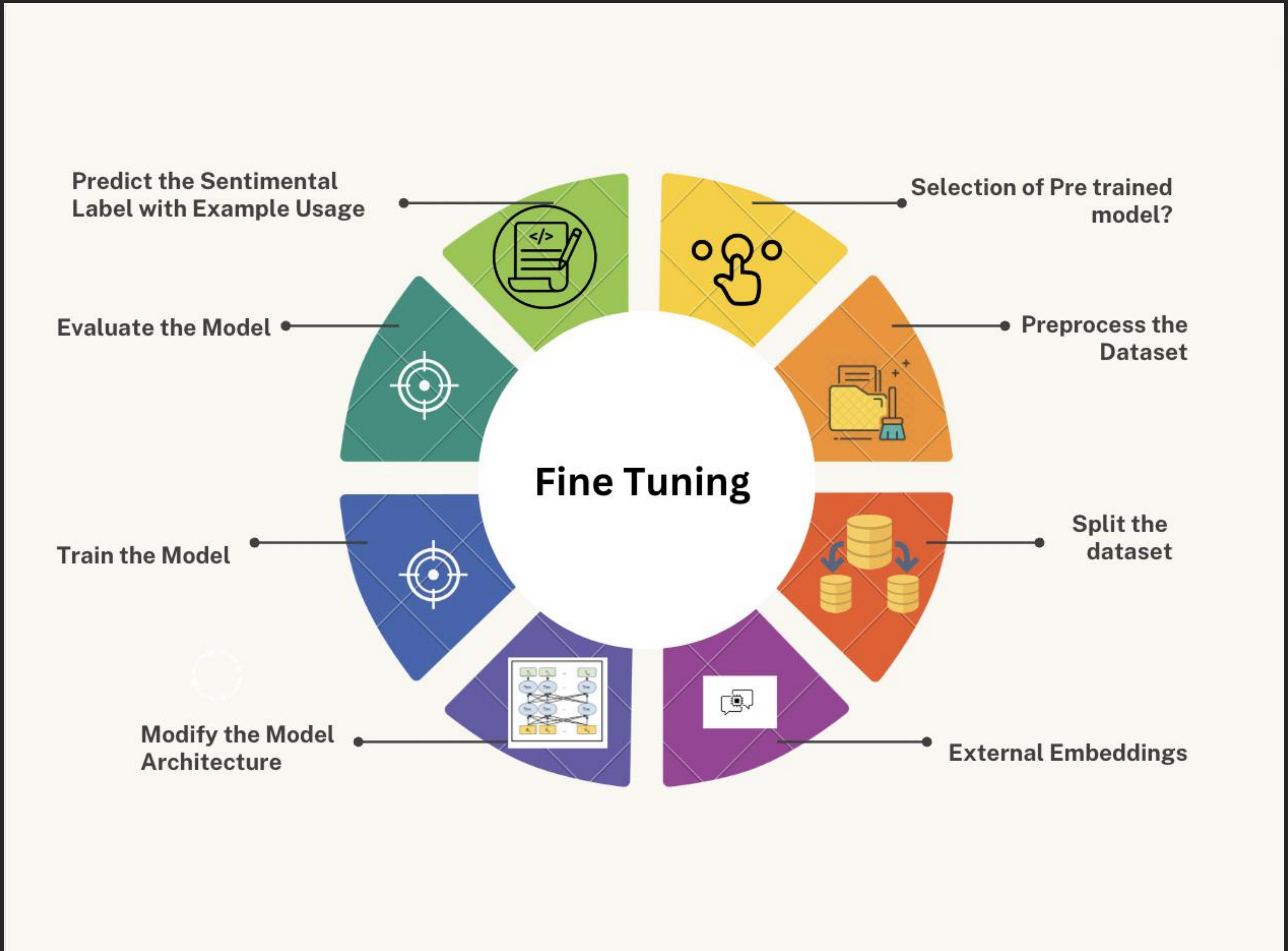
- Firstly, trained & evaluated it on tiny subset
- Then on complete dataset.

Few issues faced during this process:

- Kernel frequently died
- Dataset size mattered.
- Access to high performance computing systems (University Big Red & Deep Learning Outage)

Types of Models

- Recreated the models given in research paper. (https://arxiv.org/abs/2011.10426 )
- Fine tuned on BERT Multilingual & on PhoBert by adding extra layers (hyper parameter tuning)




Selecting a Pre-trained Model

- PhoBERT (https://huggingface.co/vinai/phobert-base)
- BERT base multilingual model (https://huggingface.co/google-bert/bert-base-multilingual-cased)

Preprocess and splitting the dataset

- No duplicates found.
- Dropped null values.
- Removed the stop words.
- The data was split into an 80-20 ratio.

Embeddings

- https://nlp.stanford.edu/projects/glove/

  Common Crawl (840B tokens, 2.2M vocab, cased, 300d vectors, 2.03 GB download)
- BERT embeddings (contextual embeddings)
- FastText ([illegible])

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- fastText (https://github.com/facebookresearch/fastText/blob/master/docs/crawl-vectors.md)

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# Predict the sentiment label using example usage

[21]:
```python
# Example usage
text = "I hate the  movie I did not like it at all"
prediction = predict_sentiment(text, model, tokenizer)
print("Predicted sentiment:", "Positive" if prediction == 1 else "Negative")
```

```
Predicted sentiment: Negative
```

[22]:
```python
# Example usage
text = '''"Aaaaand The Star Buoy hits it out of the park yet again!

What a hilarious ride. Tillu is a true blue phenomenon in the realm of Telugu Cinema 💙
And nobody can do justice to it like Siddu!
What energy, what charm ❤

Tillu is not to be reviewed, questioned, or analyzed. He is simply meant to be loved,
so gooo watch and enjoy the fun partyyy! The one-liners and Anupama(superbly written - stellar performance)
are the other standouts in this Siddu Jonnalagadda  bonanza 🎉 Don'tttt missss!"'''
prediction = predict_sentiment(text, model, tokenizer)
print("Predicted sentiment:", "Positive" if prediction == 1 else "Negative")
```

```
Predicted sentiment: Positive
```

Section 5

# Experiments

# Experiments

### Experimental Design and Setup

1. **Preprocessing Included Removal**: All models used data cleaning, such as removing stop words and duplicates.
2. **Model Selection Criteria**: Models were chosen based on their language compatibility and performance benchmarks.
3. **Training Protocols Established**: Training involved multiple epochs, utilizing cross-validation to ensure robustness.

### Datasets Used

- **Diverse Dataset Utilization**: Models were trained on datasets like IMDB reviews and Vietnamese hotel reviews.
- **Validation Methods**: Employed cross-validation techniques to assess model generalization across different datasets.

| Dataset | Train | | Test | |
|---|---|---|---|---|
| | Positive | Negative | Positive | Negative |
| IMDB | 19961 | 20039 | 5039 | 4961 |
| Vietnamese | 20493 | 20268 | 5000 | 5000 |

### Model Configurations

1. **Base and Fine-Tuned Models**: Both standard and fine-tuned versions of BERT were used to compare performance.
2. **Integration with LSTM**: Models incorporated LSTM layers to enhance learning sequential patterns in text.
3. **Architecture Specifics Detailed**: Configurations included adjustments in layers and parameters for optimal training.

### Training Process

1. **Use of High-Performance Computing**: Models required substantial computational resources for training.
2. **Challenges in Training**: Encountered issues like kernel crashes due to intensive computation demands.
3. **Training Duration**: Training times varied, with adjustments made based on the preliminary results and computational limits.

### Evaluation Metrics

1. **Accuracy and Precision**: Metrics focused on how precisely models predicted sentiment categories.
2. **Recall and F1 Score**: These metrics helped evaluate the models' ability to identify all relevant instances.
3. **Consistent Metric Application**: All models were evaluated using the same criteria for fair comparison.

### Baseline Comparisons

1. **Comparison Against Previous Models**: Baseline models included earlier versions of BERT and other NLP frameworks.
2. **Benchmarking Against Industry Standards**: Compared results with published benchmarks to validate improvements.
3. **Performance Enhancements Noted**: Detailed analysis of how fine-tuning and model adjustments outperformed baselines.

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Section 6

# Results

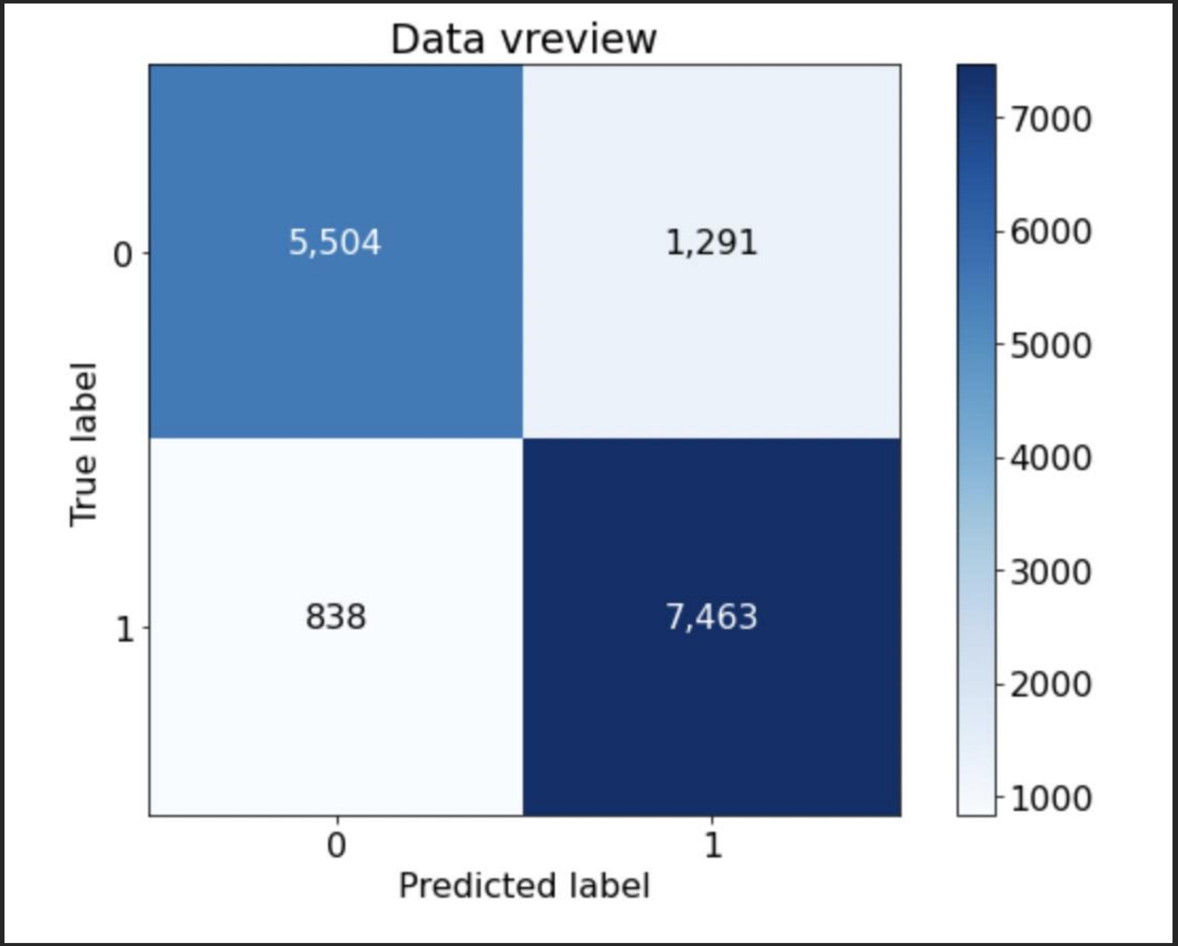
# Fine-Tune BERT-Base, Multilingual Cased

TABLE 5. RESULT OF OUR MODEL ON NTC-SV DATASET COMPARED TO OTHER MODELS

| Model | Precision(%) | Recall(%) | F1(%) |
|---|---|---|---|
| SVM | 89.23 | 92.52 | 90.84 |
| XGBoost | 88.76 | 90.58 | 89.63 |
| FastText + TextCNN | 67.9 | 89.1 | 77.1 |
| FastText + LSTM | 88.5 | 89.7 | 89.1 |
| FastText + RCNN | 89.2 | 91.7 | 90.4 |
| Glove + TextCNN | 69.7 | 87.7 | 77.7 |
| Glove + LSTM | 88.7 | 91.8 | 89.8 |
| Glove + RCNN | 85.8 | 85.8 | 90.7 |
| BERT-base | 88.13 | **94.02** | 90.9 |
| BERT-LSTM | **89.78** | 92.08 | 90.91 |
| BERT-TextCNN | 88.85 | 93.14 | 90.94 |
| BERT-RCNN | 88.76 | 93.68 | **91.15** |

| Models (epoch = 5) | Datasets | | | |
|---|---|---|---|---|
| | Vietnamese | | | |
| | Accuracy | Precision | Recall | F1 |
| Fine-Tune BERT-Base, Multilingual Cased | 0.8296 | 0.8097 | 0.8618 | 0.8349 |
| Fine-Tune BERT-Base, Multilingual Cased + LSTM | 0.8515 | 0.7737 | 0.8547 | 0.8122 |

# BERT-Base, Multilingual Cased




| Models (epoch = 5) | Datasets | | | |
|---|---|---|---|---|
| | Vietnamese | | | |
| | Accuracy | Precision | Recall | F1 |
| BERT-Base, Multilingual Cased | **0.8932** | **0.8795** | **0.9112** | **0.8951** |
| BERT-Base, Multilingual Cased + LSTM | 0.7564 | 0.7459 | 0.7806 | 0.7629 |

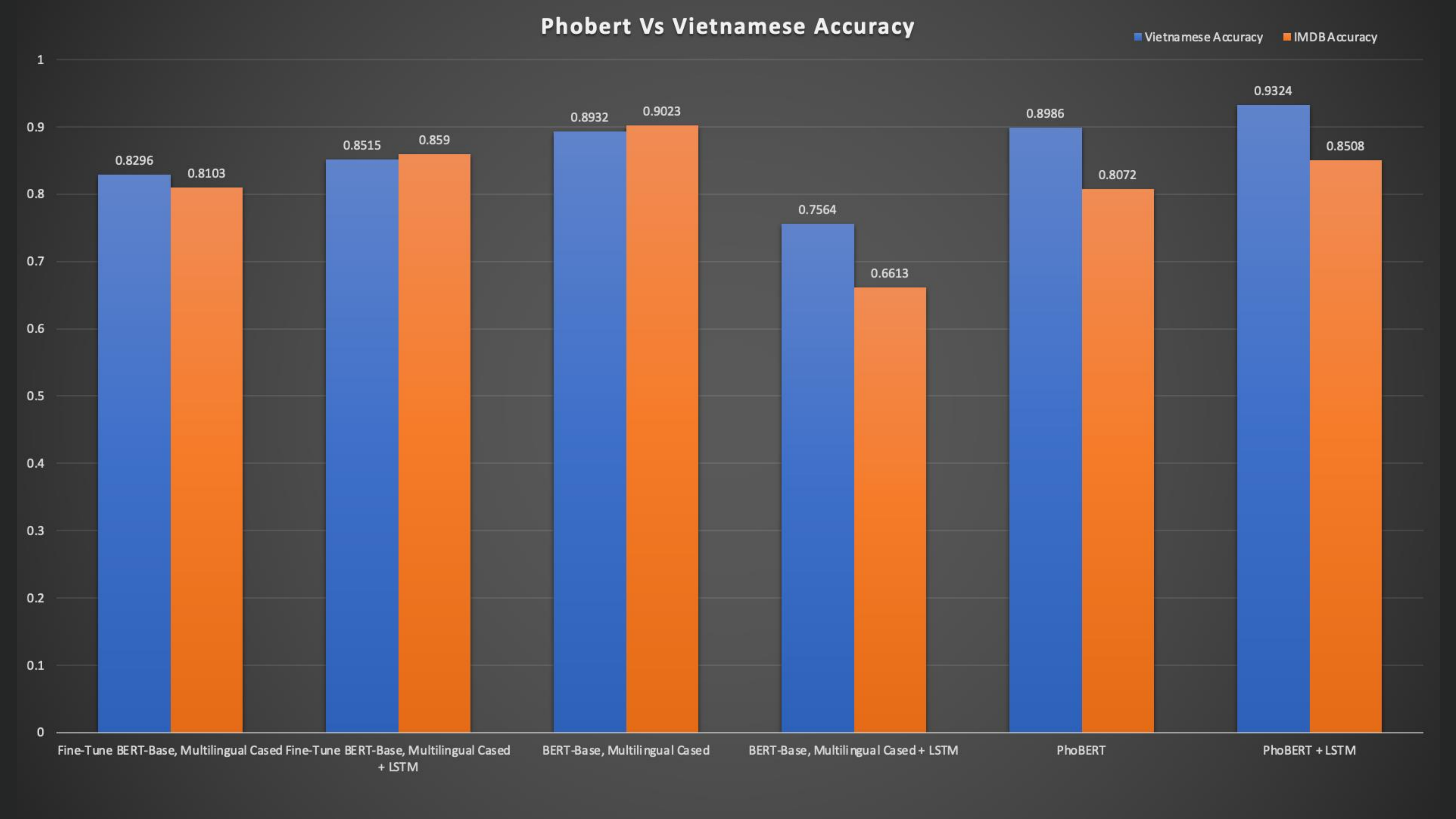
# Fine-Tune BERT-Base, Multilingual Cased

## Original PhoBERT-base Results:

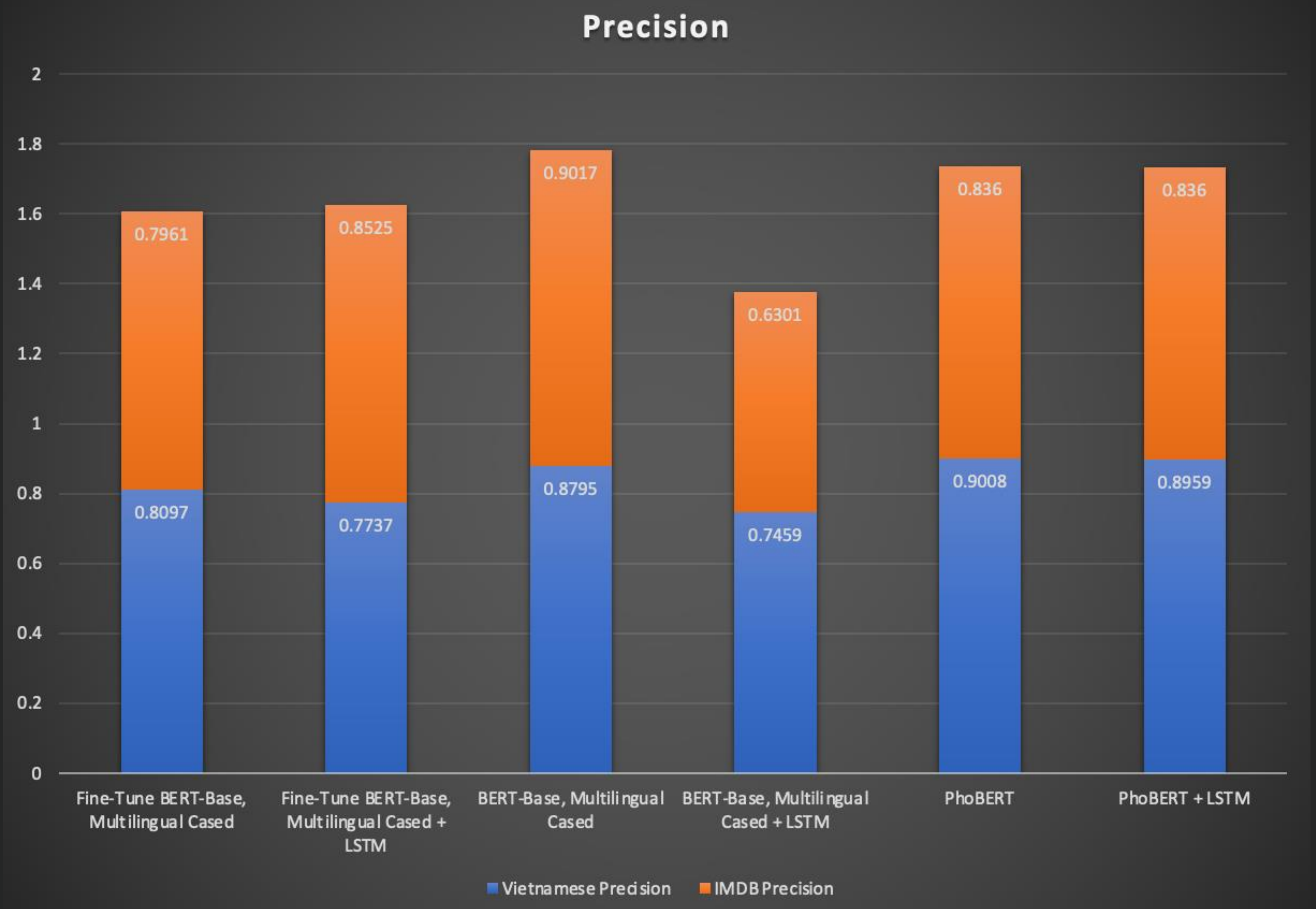
**Accuracy: 96.7%**
**F1 Score: 93.6%**

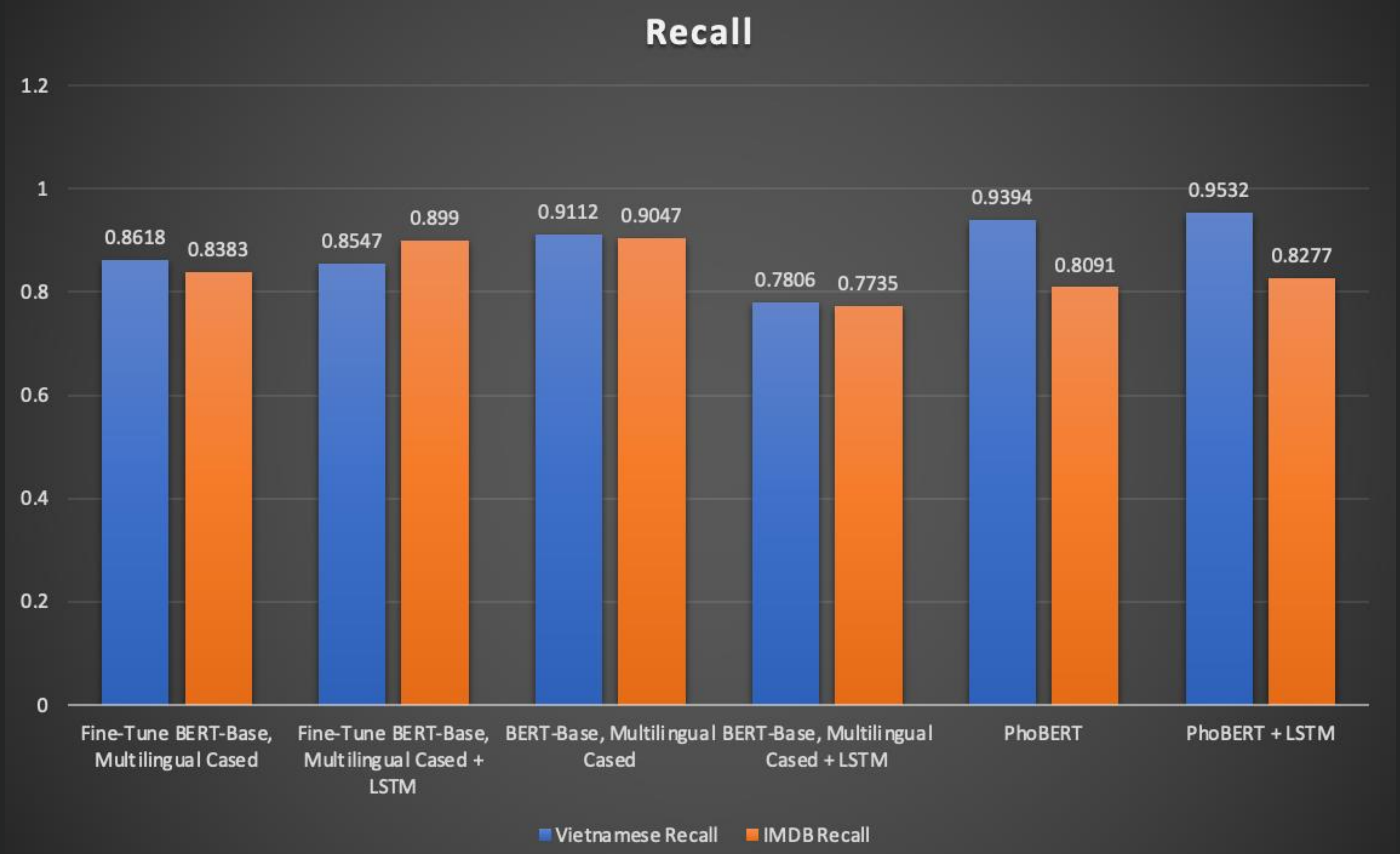
| Models (epoch = 5) | Datasets | | | |
|---|---|---|---|---|
| | Vietnamese | | | |
| | Accuracy | Precision | Recall | F1 |
| PhoBERT | 0.8986 | 0.9008 | 0.9394 | 0.9197 |
| PhoBERT + LSTM | 0.9324 | 0.8959 | 0.9532 | 0.9236 |

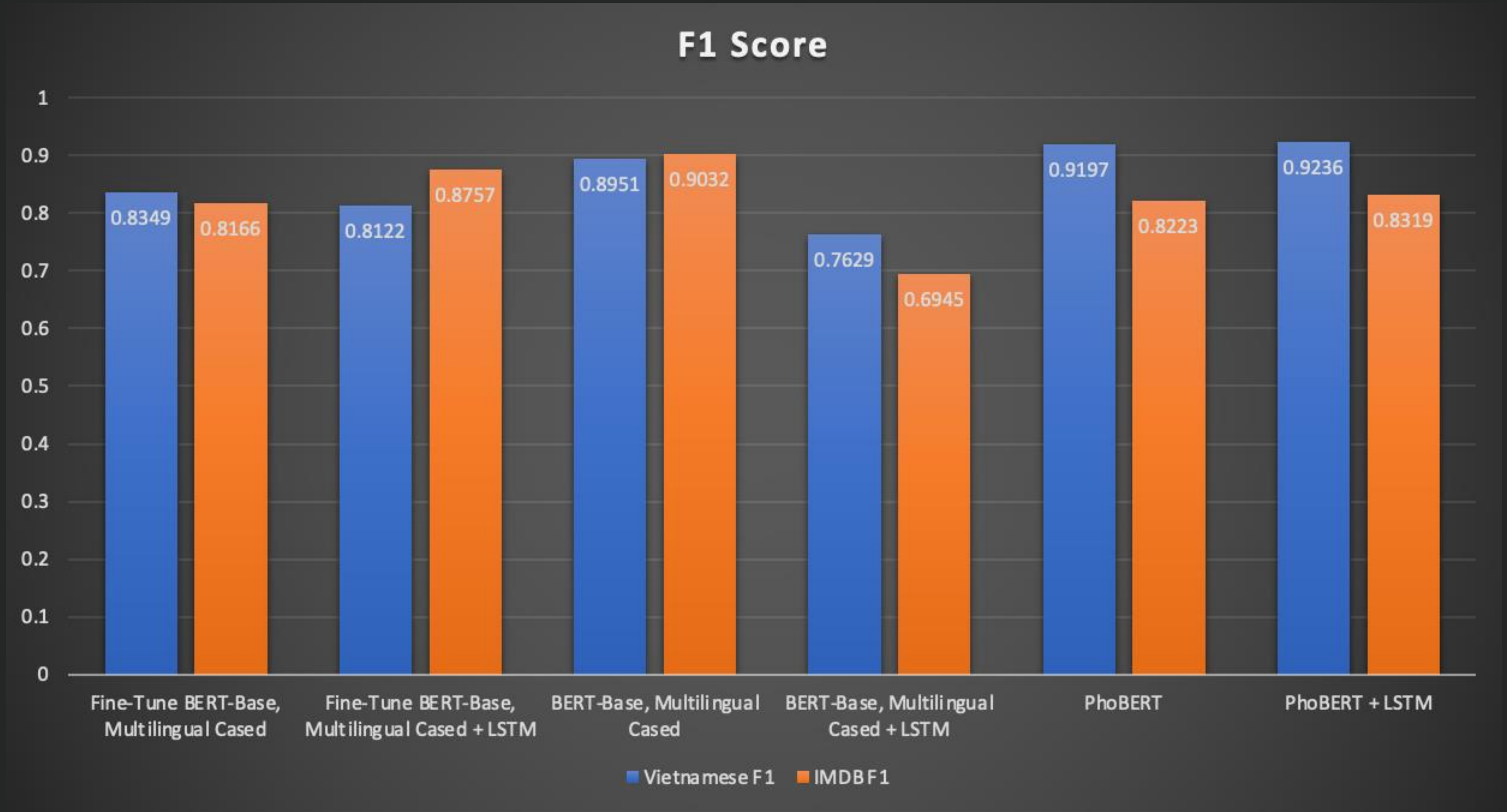
| Models (epoch = 5) | Datasets | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Vietnamese | | | | English | | | |
| | Accuracy | Precision | Recall | F1 | Accuracy | Precision | Recall | F1 |
| **Fine-Tune BERT-Base, Multilingual Cased** | 0.8296 | 0.8097 | 0.8618 | 0.8349 | 0.8103 | 0.7961 | 0.8383 | 0.8166 |
| **Fine-Tune BERT-Base, Multilingual Cased + LSTM** | 0.8515 | 0.7737 | 0.8547 | 0.8122 | 0.859 | 0.8525 | 0.8990 | 0.8757 |
| **BERT-Base, Multilingual Cased** | 0.8932 | 0.8795 | 0.9112 | 0.8951 | 0.9023 | 0.9017 | 0.9047 | 0.9032 |
| **BERT-Base, Multilingual Cased + LSTM** | 0.7564 | 0.7459 | 0.7806 | 0.7629 | 0.6613 | 0.6301 | 0.7735 | 0.6945 |
| **PhoBERT** | 0.8986 | 0.9008 | 0.9394 | 0.9197 | 0.8072 | 0.836 | 0.8091 | 0.8223 |
| **PhoBERT + LSTM** | 0.9324 | 0.8959 | 0.9532 | 0.9236 | 0.8508 | 0.836 | 0.8277 | 0.8319 |



Phobert Vs Vietnamese Accuracy
Vietnamese Accuracy
IMDB Accuracy
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.8296
0.8103
0.8515
0.859
0.8932
0.9023
0.7564
0.6613
0.8986
0.8072
0.9324
0.8508
Fine-Tune BERT-Base, Multilingual Cased
Fine-Tune BERT-Base, Multilingual Cased + LSTM
BERT-Base, Multilingual Cased
BERT-Base, Multilingual Cased + LSTM
PhoBERT
PhoBERT + LSTM


Precision
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0.7961
0.8097
0.8525
0.7737
0.9017
0.8795
0.6301
0.7459
0.836
0.9008
0.836
0.8959
Fine-Tune BERT-Base, Multilingual Cased
Fine-Tune BERT-Base, Multilingual Cased + LSTM
BERT-Base, Multilingual Cased
BERT-Base, Multilingual Cased + LSTM
PhoBERT
PhoBERT + LSTM
Vietnamese Precision
IMDB Precision

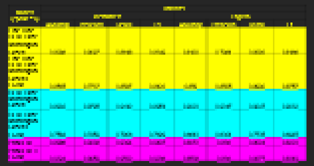

Recall
1.2
1
0.8
0.6
0.4
0.2
0
0.8618
0.8383
0.8547
0.899
0.9112
0.9047
0.7806
0.7735
0.9394
0.8091
0.9532
0.8277
Fine-Tune BERT-Base, Multilingual Cased
Fine-Tune BERT-Base, Multilingual Cased + LSTM
BERT-Base, Multilingual Cased
BERT-Base, Multilingual Cased + LSTM
PhoBERT
PhoBERT + LSTM
Vietnamese Recall
IMDB Recall



F1 Score
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.8349
0.8166
0.8122
0.8757
0.8951
0.9032
0.7629
0.6945
0.9197
0.8223
0.9236
0.8319
Fine-Tune BERT-Base, Multilingual Cased
Fine-Tune BERT-Base, Multilingual Cased + LSTM
BERT-Base, Multilingual Cased
BERT-Base, Multilingual Cased + LSTM
PhoBERT
PhoBERT + LSTM
Vietnamese F1
IMDB F1

Section 7

# Analysis & Conclusion



# Analysis & Conclusion

## Performance Analysis

1. PhoBERT models outperform Google BERT on both English and Vietnamese datasets.
2. LSTM integration improves recall but may slightly decrease precision in some models.
3. PhoBERT with LSTM shows the best overall performance, particularly in F1 score.

## Model Effectiveness

1. PhoBERT is more effective across languages, showcasing strong cross-lingual capabilities.
2. BERT models demonstrate high recall, indicating better capture of relevant sentiment.
3. The addition of LSTM consistently enhances sentiment detection in diverse datasets.

## Challenges and Limitations

| Model Name | Original Optimization Parameters | | | In this Project Optimization Activities | | |
|---|---|---|---|---|---|---|
| | Epochs | Max Length | #params | Epochs | Max Length | #params |
| BERT-Base, Multilingual Cased | 40 | 512 | 179M | 5 | 512 | 179M |
| Fine-Tune BERT-Base, Multilingual Cased | 10 | 256 | 179M | 5 | 256 | 179M |
| PhoBERT | 40 | 256 | 135M | 5 | 256 | 135M |

1. Multilingual BERT underperforms compared to monolingual PhoBERT in language-specific tasks.
2. Integrating LSTM shows varied results, suggesting potential overfitting or bias in certain contexts.
3. Computational constraints may limit the extent of fine-tuning and model complexity.

## Theoretical Implications

1. The results affirm the importance of language-specific models for sentiment analysis tasks.
2. The effectiveness of LSTM implies sequential data processing is critical for sentiment analysis.
3. The strong performance of PhoBERT suggests that contextualized embeddings play a key role in NLP.

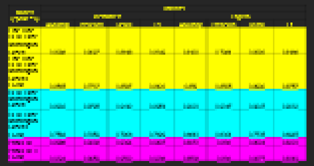
## Practical Applications

1. PhoBERT could be used in customer service bots for sentiment recognition across languages.
2. Models with LSTM can improve sentiment-based recommendation systems in e-commerce.
3. Fine-tuned BERT models are applicable for social media monitoring in multiple languages.

## Future Work and Improvements

1. Further exploration of hyperparameter tuning could enhance model accuracies.
2. Investigate models' performance on a wider range of languages and domains.
3. Develop lightweight models to address computational constraints and enhance accessibility.

# Performance Analysis



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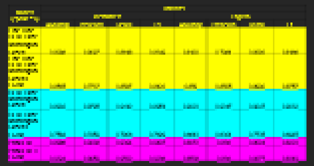

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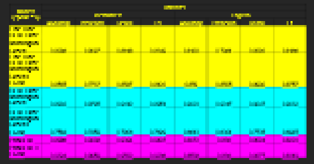

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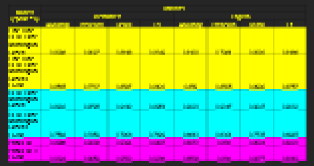

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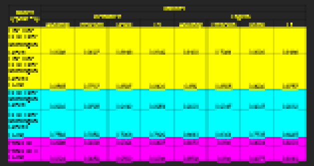

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# Reference

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# Questions?

# Thank You!