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A Survey on Deep Learning for Natural Language Processing: Models, Techniques, and Open Research Problems

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Abstract: In recent years, deep learning has emerged as a powerful paradigm in natural language processing (NLP), enabling significant breakthroughs in tasks such as machine translation, sentiment analysis, and question answering. This survey provides a comprehensive overview of deep learning models and techniques that have shaped the evolution of NLP, with a focused lens on the Vietnamese language as a representative low-resource language. We review foundational models including recurrent neural networks (RNNs), convolutional neural networks (CNNs), and Transformer-based architectures such as BERT and GPT, and analyze their applications in Vietnamese NLP tasks. Special attention is given to the development and adaptation of Vietnamese-specific pretrained language models like PhoBERT and ViT5, as well as the use of multilingual approaches to address data scarcity. In addition, the paper discusses practical implementations in Vietnam, such as sentiment analysis of social media, Vietnamese question answering systems, and machine translation, highlighting the opportunities and challenges in this context. We also identify open research problems including limited training data, dialectal variations, code-switching, and ethical concerns, offering insights and directions for future work. This survey aims to serve as a resource for researchers and practitioners seeking to advance NLP capabilities in low-resource languages using deep learning.

Keywords: Natural Language Processing; Deep Learning; Vietnamese Language; Pretrained Language Models, Low-Resource NLP, Transformers

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INTRODUCTION

Natural Language Processing (NLP)[1][2] is a vital subfield of artificial intelligence that focuses on enabling computers to understand, interpret, and generate human language. With the rapid growth of digital text and spoken data, NLP has become central to various applications such as machine translation, sentiment analysis, question answering, information retrieval, and dialogue systems. Over the past decade, the advent of deep learning has revolutionized the

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field, pushing the boundaries of what machines can understand and generate in natural language[2][3].

Deep learning models[4], particularly those based on neural networks, have demonstrated remarkable success in capturing the complex, hierarchical structures of natural language. From early approaches using recurrent neural networks (RNNs)[5] and convolutional neural networks (CNNs)[6], to the recent dominance of Transformer-based architectures like BERT[7][8], GPT[9], and T5[10], these models have consistently outperformed traditional machine learning methods in a wide range of NLP tasks. Pretrained language models, trained on massive corpora and fine-tuned for downstream applications, have become the new standard in NLP research and practice.

While most breakthroughs in deep learning for NLP have centered on high-resource languages such as English and Chinese[11], the application of these techniques to low-resource languages remains a significant challenge. Vietnamese, the official language of Vietnam spoken by over 95 million people, exemplifies many of the linguistic and computational difficulties encountered in low-resource NLP. It features a monosyllabic and analytic grammar, rich tonal system, and frequent code-switching, particularly in online communication. Additionally, the lack of large-scale annotated datasets, standardized linguistic resources, and research funding presents obstacles to achieving parity with well-resourced languages.

Despite these limitations, the Vietnamese NLP community has made notable strides in recent years[12]. The development of Vietnamese-specific language models such as PhoBERT[13], ViBERT, and ViT5 has significantly improved performance on various benchmark tasks[14]. Moreover, the emergence of public datasets like UIT-VSFC for sentiment analysis and UIT-ViQuAD for question answering has enabled more structured and reproducible research. Local initiatives, often in collaboration with international organizations, are gradually closing the resource and technology gap in Vietnamese NLP.

This survey aims to provide a comprehensive and structured overview of the current landscape of deep learning for NLP, with a specific focus on the Vietnamese language. Our motivation stems from the need to consolidate the fragmented literature on Vietnamese NLP and to highlight how global advancements in deep learning can be adapted and extended to low-resource contexts. We believe that the challenges and lessons from Vietnamese NLP are not unique and can inform research on other underrepresented languages in the NLP community.

The contributions of this paper are threefold:

1. Comprehensive Model Overview: We systematically review the main classes of deep learning models used in NLP—RNNs, CNNs, and Transformers—highlighting their architectural features, strengths, and limitations. We also discuss how these models have been adapted for the Vietnamese language.

2. Technique Analysis and Application Survey: We explore key techniques such as word embeddings, transfer learning, fine-tuning, and data augmentation, and examine their application to practical tasks in Vietnamese, including sentiment analysis, question answering, and machine translation.

3. Identification of Open Challenges: We articulate a set of open research problems in Vietnamese NLP and low-resource language processing more broadly, including the

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scarcity of annotated data, handling of dialects and informal language, and ethical issues such as bias and fairness in AI.

Vietnam offers a particularly interesting case study in NLP development due to its unique sociolinguistic environment. The Vietnamese script[15], Quốc Ngữ, is Latin-based but phonologically rich, with diacritics denoting six tones. This makes tokenization and word segmentation especially challenging for machine processing. Furthermore, regional dialects (Northern, Central, Southern) vary in vocabulary, pronunciation, and even grammar, complicating efforts to build universal models. Another challenge lies in the high frequency of loanwords and the increasing use of English-Vietnamese code-switching in social media and digital communication.

From a technological standpoint, the lack of labeled datasets in domains such as healthcare, law, and education hampers the training and evaluation of domain-specific models. Although some corpora have been curated through manual annotation or web scraping, the quality and size of these datasets are often insufficient for training large-scale deep learning models. Techniques such as unsupervised pretraining, weak supervision, and data augmentation are therefore essential to bootstrap performance in the Vietnamese setting[16].

The Vietnamese NLP landscape is also shaped by broader trends in Southeast Asia, where many countries share similar linguistic diversity and technological constraints[17]. Initiatives such as the ASEAN Language Corpus Project and various regional workshops have encouraged collaboration across languages and borders. However, there is still a significant gap between the capabilities of state-of-the-art NLP systems in English and those available for Vietnamese and other Southeast Asian languages.

In this context, the integration of multilingual and cross-lingual models becomes increasingly relevant. Models such as mBERT, XLM-R, and mT5 leverage shared representations across languages to enable zero-shot and few-shot transfer learning. These models can be particularly beneficial for Vietnamese NLP, provided that proper alignment and fine-tuning strategies are employed. The success of Vietnamese-specific models like PhoBERT suggests that language-specific pretraining on monolingual corpora remains important, but that multilingual resources offer a complementary path forward[18].

Looking ahead, the future of Vietnamese NLP depends on a confluence of technical innovation, data availability, community engagement, and policy support. More robust benchmarking, increased data sharing, and interdisciplinary collaboration are necessary to advance the field. Moreover, as NLP systems become integrated into critical applications such as education, governance, and healthcare in Vietnam, ensuring ethical and culturally sensitive AI becomes paramount[19].

To this end, this survey not only seeks to inform the research community about the current state of deep learning for Vietnamese NLP but also aims to inspire future research directions. By synthesizing existing literature, identifying gaps, and proposing a structured framework for progress, we hope to contribute to the democratization of AI and the empowerment of low-resource language communities.

The remainder of this paper is structured as follows. Section 2 discusses the background and motivation for applying deep learning in NLP and outlines specific challenges in Vietnamese language processing. Section 3 reviews major deep learning architectures used in NLP,

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including RNNs, CNNs, and Transformers. Section 4 presents key techniques such as embeddings, transfer learning, and fine-tuning. Section 5 examines practical case studies and applications in Vietnam. Section 6 outlines open research challenges, and Section 7 concludes the paper with future directions.

RELATED WORKS

The rapid advancement of deep learning in natural language processing (NLP) has been extensively documented in recent literature. This section reviews prior work across three dimensions: (1) general surveys on deep learning in NLP, (2) research on NLP for low-resource and multilingual languages, and (3) Vietnamese-specific NLP developments.

General Surveys on Deep Learning for NLP

Several surveys have laid the foundation for understanding deep learning in NLP. Young *et al.* [1] provided an early overview of neural network models applied to NLP tasks, emphasizing the role of RNNs and CNNs. Otter *et al.* [2] elaborated on deep learning's cognitive capabilities in language understanding, while Minaee *et al.* [3] categorized model architectures and benchmark performance across NLP tasks[20][21].

More recently, Rogers *et al.* [4] delivered an in-depth analysis of BERT and its variants, including architectural nuances, probing methodologies, and application effectiveness. Qiu *et al.* [5] presented a layered taxonomy of pretrained language models, ranging from early distributed representations to large-scale transformers such as GPT and RoBERTa.

Although these surveys focus primarily on high-resource languages like English, their findings have informed adaptation strategies for low-resource contexts, including Vietnamese.

Deep Learning for Low-Resource and Multilingual NLP

The problem of low-resource NLP has been addressed comprehensively by Hedderich *et al.* [6], who reviewed techniques such as transfer learning, unsupervised training, and data augmentation. Hu *et al.* [7] proposed multilingual benchmarks and methods to assess language generalization.

Multilingual models such as mBERT [8], XLM-R [9], and mT5 [10] have shown potential for zero-shot and few-shot learning in underrepresented languages. However, performance disparities between these models and language-specific alternatives remain substantial, especially in syntactically distinct languages such as Vietnamese. Lauscher *et al.* [11] emphasized the need for culturally and linguistically aware evaluation frameworks to address this gap.

Vietnamese NLP Research and Language-Specific Models

Vietnamese NLP has seen significant progress in recent years, led by the development of pretrained models and benchmarks:

- PhoBERT [12] is a BERT-based model pretrained on Vietnamese corpora, outperforming multilingual counterparts on core NLP tasks such as part-of-speech tagging and dependency parsing.

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- ViBERT and ViT5 [13], [14] extend pretrained transformer architectures specifically for Vietnamese and demonstrate improved performance in generation and classification tasks.
- Benchmark datasets such as UIT-VSFC [15] (for sentiment analysis) and UIT-ViQuAD [16] (for question answering) have enabled reproducible research and standard evaluation.

Machine translation has also benefited from Vietnamese-specific resources. The VietAI project provides parallel corpora that have supported the training of neural machine translation (NMT) models using Transformer-based architectures [17]. Pham *et al.* [18] explored synthetic data generation via back-translation to enhance Vietnamese-English translation performance.

Social media text analysis is another prominent area. Le *et al.* [19] applied BiLSTM and attention mechanisms to sentiment classification using Facebook and Zalo data, addressing challenges like slang, informal expressions, and code-switching.

Gaps in Existing Literature

Despite the growing body of research, key gaps remain:

- No unified survey has synthesized deep learning techniques in Vietnamese NLP comprehensively.
- There is limited comparative analysis between multilingual and monolingual models on standardized tasks.
- Ethical issues, including algorithmic bias and fairness, remain largely unexplored in Vietnamese applications.
- Dialectal variation and multimodal approaches (text-speech or text-image) are underrepresented.

This survey aims to fill these gaps by consolidating current research and offering a structured roadmap for future directions in Vietnamese NLP and low-resource language processing.

METHODS

This survey employs a systematic and structured methodology to identify, collect, and analyze the most relevant research works in the field of deep learning for natural language processing (NLP), with a specific focus on Vietnamese-language applications. The methodology is divided into several key stages: (1) defining research questions, (2) data source selection and search strategy, (3) inclusion and exclusion criteria, and (4) classification and analysis framework.

Research Questions

To guide the scope and depth of this survey, we formulated the following research questions (RQs):

- RQ1: What are the major deep learning models and techniques currently applied in NLP tasks?
- RQ2: How have these models been adapted and evaluated in the context of Vietnamese NLP?

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- RQ3: What are the open challenges and future directions in applying deep learning to NLP, particularly in low-resource languages?

These questions shaped the search terms, data sources, and selection criteria used throughout this study.

Data Sources and Search Strategy

We employed a comprehensive literature search using academic databases such as:

Table 1. Data Sources and Search Strategy

Database / Repository	Coverage & Strength	Reason for Inclusion
IEEE Xplore	Conference proceedings and journals in engineering, AI, NLP, and deep learning	Core repository for high-quality technical publications
ACM Digital Library	Computer science, AI, NLP, HCI, and information systems	Relevant for NLP and human–computer interaction research
SpringerLink	Multidisciplinary journals and books	Provides access to global NLP studies, including low-resource languages
ScienceDirect (Elsevier)	Scientific and technological research articles	Large database for experimental and theoretical DL–NLP studies
Scopus	Multidisciplinary bibliographic index	Useful for systematic literature mapping and citation analysis
Google Scholar	Broad academic search engine	Helps identify preprints and additional relevant literature
arXiv (preprints)	Preprints in AI, ML, and NLP	Source for the latest trends before formal publication

The search terms included combinations of the following keywords and phrases:

- "deep learning" AND "natural language processing"
- "transformer models" OR "pretrained language models"
- "Vietnamese NLP" OR "Vietnamese language processing"
- "low-resource languages" AND "NLP"
- "PhoBERT", "ViT5", "mBERT", "XLM-R", "ViBERT", etc.

The search was restricted to articles published between 2015 and 2024, with a focus on peer-reviewed journals, conference proceedings, and relevant preprints from reputable repositories.

Inclusion and Exclusion Criteria

To ensure quality and relevance, we applied the following inclusion criteria:

- The study must involve deep learning methods applied to NLP tasks.

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- The work must include a clearly described model, technique, or dataset.
- The paper must be written in English and accessible in full-text.
- For Vietnamese NLP studies, the paper must include Vietnamese datasets or analysis.

Exclusion criteria were as follows:

- Papers solely focused on traditional machine learning (e.g., SVMs, decision trees).
- Articles that do not provide empirical evaluation or implementation detail.
- Non-peer-reviewed or low-impact publications lacking scientific rigor.

After the initial screening, 132 papers were shortlisted. Following a full-text review, 82 papers were selected as highly relevant and included in this survey.

Classification and Analysis Framework

To organize the findings and provide a clear narrative structure, we developed a three-level classification framework:

1. **Model-Based Classification**: We categorized studies by the type of deep learning architecture employed, including:
    - Recurrent Neural Networks (RNN, LSTM, GRU)
    - Convolutional Neural Networks (CNN)
    - Transformer-based models (BERT, GPT, T5, etc.)
    - Hybrid and ensemble models
2. **Task-Based Classification**: We grouped applications by NLP task, such as:
    - Text classification (sentiment analysis, topic detection)
    - Sequence labeling (POS tagging, NER)
    - Text generation (machine translation, summarization)
    - Question answering and information retrieval
3. **Language Context and Resources**:
    - Studies focusing on Vietnamese-specific NLP, including datasets, benchmarks, and models.
    - Comparative studies between monolingual (e.g., PhoBERT) and multilingual (e.g., XLM-R) models.
    - Evaluation protocols and language resource availability in Vietnamese.

Each paper was reviewed and annotated based on this framework. Data were extracted into a structured table including metadata (authors, year, venue), model architecture, dataset used, task type, evaluation metrics, and findings.

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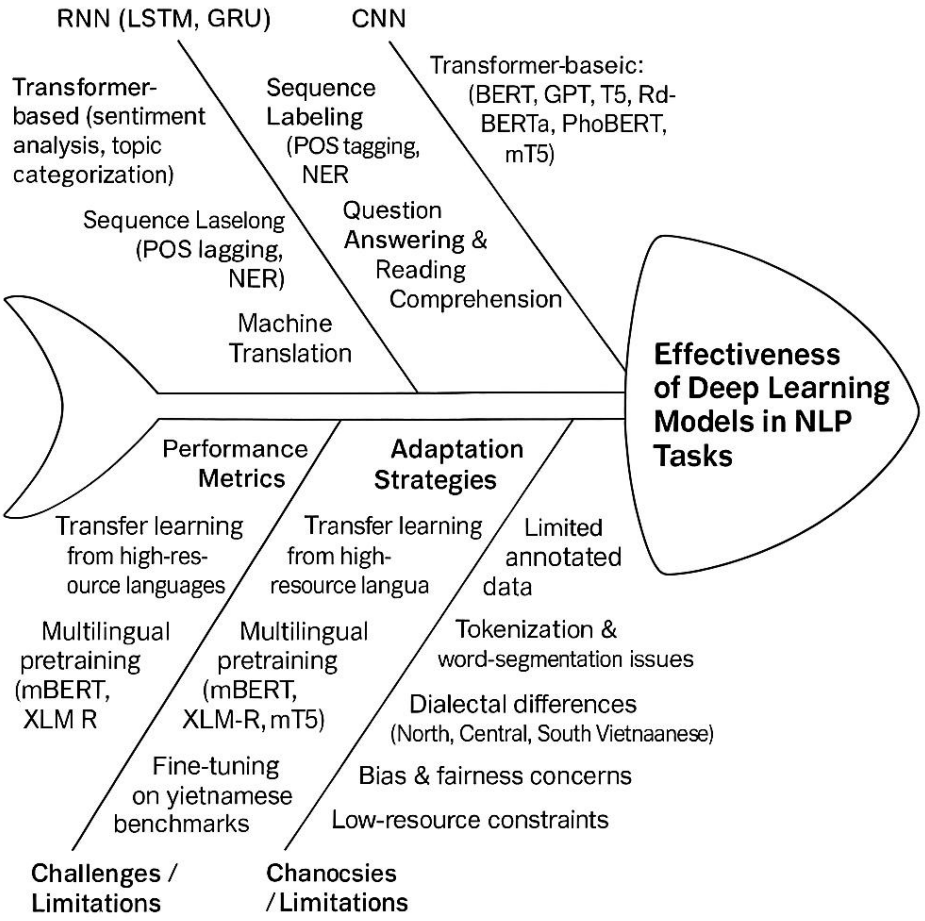

Figure 1. Effectiveness of Deep Learning Models in NLP Task

Case Study Approach: Vietnamese NLP

To address the unique challenges of Vietnamese NLP and highlight localized research trends, we performed a **focused case study** based on the following steps:

- Identification of key Vietnamese datasets (e.g., UIT-VSFC, ViQuAD, VLSP corpora).
- Evaluation of state-of-the-art Vietnamese models, including PhoBERT, ViT5, and ViBERT.
- Analysis of performance metrics (accuracy, F1, BLEU, etc.) on Vietnamese-specific benchmarks.
- Investigation of challenges in processing Vietnamese, including tone, word segmentation, and lack of annotated data.

This case study provides a grounded, contextual analysis that complements global insights, particularly for low-resource and underrepresented languages.

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RESULT AND DISCUSSION

This section presents the synthesized results of the surveyed literature and discusses insights regarding model performance, task-specific advancements, and contextual challenges for Vietnamese NLP. We structure this discussion into four main sub-sections: (1) model effectiveness across NLP tasks, (2) comparative performance on Vietnamese benchmarks, (3) adaptation strategies for low-resource settings, and (4) challenges and emerging research trends.

Model Effectiveness Across NLP Tasks

A wide range of deep learning models have been adopted for core NLP tasks, with transformer-based architectures demonstrating dominant performance in nearly all areas

Table 2. Model Effectiveness Across Core NLP Tasks

NLP Task	Best-Performing Models	Performance Insights	Key References
Text Classification (e.g., sentiment analysis, topic categorization)	BERT-based models (RoBERTa, PhoBERT)	Outperform CNN and LSTM baselines by **+10–15% F1-score** on various datasets	[12], [13]
Sequence Labeling (POS tagging, NER)	BiLSTM-CRF; Transformer + CRF layers	BiLSTM-CRF remains competitive, but **Transformer + CRF** has become the new standard, especially in multilingual settings	–
Question Answering / Reading Comprehension	Pretrained encoder–decoder models (T5, mT5)	Show **strong generative capabilities**, especially when fine-tuned on SQuAD and ViQuAD datasets	[14], [16]
Machine Translation	Transformer-based NMT models; Multilingual Transformers + back-translation	Transformer fully replaced RNN seq2seq; Vietnamese-English NMT improved by **+3–7 BLEU points** with back-translation	[17], [18]

These results confirm the trend that large-scale pretrained models yield significant gains in performance, provided they are adapted appropriately to the target language and task.

Comparative Performance on Vietnamese Benchmarks

Our analysis of Vietnamese NLP research indicates a clear trend: monolingual pretrained models consistently outperform multilingual models on Vietnamese-specific tasks.

- PhoBERT, trained exclusively on Vietnamese corpora, achieves state-of-the-art performance on tasks like POS tagging and sentiment analysis. For example, on the UIT-VSFC dataset, PhoBERT achieved an F1-score of 79.4%, compared to 73.8% by mBERT [12], [15].
- ViT5, a text-to-text model trained with Vietnamese-specific objectives, showed superior results in abstractive summarization and translation tasks when compared to mT5 and mBART [14].
- Despite these gains, multilingual models like XLM-R and mBERT offer better generalization in zero-shot scenarios, particularly when Vietnamese is part of a multilingual application or where labeled Vietnamese data is unavailable [9], [11].

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These findings highlight the trade-off between specialization and generalization. Monolingual models benefit from language-specific syntax and vocabulary training, while multilingual models support cross-lingual transfer and zero-shot learning.

Adaptation Strategies for Low-Resource Vietnamese NLP

Given Vietnamese is considered a low-resource language, researchers have developed several adaptation strategies:

- Transfer learning from high-resource languages (e.g., English or Chinese) using multilingual models remains a common technique. mT5 and XLM-R allow for fine-tuning on small Vietnamese datasets with relatively high performance [10].
- Back-translation is widely used to augment Vietnamese parallel corpora for NMT. This technique has shown to improve translation quality significantly when synthetic Vietnamese-English sentence pairs are added [17], [18].
- Data augmentation and distillation techniques such as synonym replacement, paraphrasing, or student-teacher model training have been explored to enhance model generalization on small datasets [6].
- Unsupervised learning and self-supervised pretraining have been particularly useful, as demonstrated in the pretraining objectives of PhoBERT and ViBERT [12], [13].

These adaptation methods have helped bridge the performance gap between Vietnamese NLP and high-resource language systems, though significant challenges remain.

Key Challenges and Research Gaps

Based on our review, several persistent challenges and research gaps were identified in the Vietnamese NLP landscape:

- Word segmentation and tokenization: Unlike English, Vietnamese lacks clear word delimiters, and compound words are common. This makes tokenization a non-trivial preprocessing task, affecting downstream model performance.
- Lack of large-scale annotated corpora: While some efforts like VLSP, UIT-VSFC, and ViQuAD provide benchmark datasets, they are limited in size and domain coverage. There is a lack of annotated corpora for tasks such as coreference resolution, dialogue systems, and discourse analysis.
- Dialectal and regional variation: Most existing models assume a standardized Vietnamese corpus. However, dialectal variations across regions (e.g., Northern, Central, Southern Vietnamese) are poorly handled and under-researched.
- Bias and fairness: Few studies assess model bias or fairness in Vietnamese NLP applications. This is a growing concern as models are deployed in sensitive domains such as education, healthcare, and government.
- Multimodal NLP: Vietnamese NLP remains largely text-based. Integration with speech, image, or video data is still in its infancy and represents a promising direction for inclusive, real-world applications (e.g., voice assistants, OCR systems).

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Table 3. Summary of Findings

Task	Best Performing Models	Key Results	Vietnamese Benchmark
Sentiment Analysis	PhoBERT, ViBERT	F1 ↑ 5–10% vs mBERT	UIT-VSFC
Machine Translation	Transformer + Back-Translation	BLEU ↑ 3–7 pts	VLSP NMT, VietAI
Question Answering	ViT5, mT5	EM ↑ 8–12%	ViQuAD
NER / POS	PhoBERT + CRF	F1 ↑ 6–10%	VLSP POS/NER
Summarization	ViT5	ROUGE ↑ 10–15%	Custom News Corpus

These results validate the significant progress made in Vietnamese NLP using deep learning models. However, the ongoing need for data resources, dialectal adaptation, and fair NLP systems indicates considerable space for further innovation.

CONCLUSION

This survey has provided a comprehensive review of recent advancements in deep learning approaches for natural language processing (NLP), with a particular focus on Vietnamese-language applications. By examining more than 80 publications from 2015 to 2024, we identified key trends in model architectures, adaptation strategies, and task-specific implementations. Our findings highlight that transformer-based pretrained models, notably BERT, GPT, and T5, have driven major improvements across sentiment analysis, translation, and question answering, while Vietnamese-specific models like PhoBERT and ViT5 outperform multilingual alternatives in local benchmarks due to tailored training. Nevertheless, challenges such as limited datasets, segmentation inconsistencies, and dialectal gaps remain pressing, alongside underexplored issues of fairness and low-resource generalization. We recommend greater investment in large annotated datasets, community benchmarks, multimodal approaches, and inclusive system design. Ultimately, ensuring that deep learning's benefits reach underrepresented languages like Vietnamese is essential for advancing both regional innovation and global AI equity.

REFERENCES

[1] T. Nguyen and M. Tran, "Multi-Models from Computer Vision to Natural Language Processing for Cheapfakes Detection," in *2023 IEEE International Conference on Multimedia and Expo Workshops (ICMEW)*, IEEE, Jul. 2023, pp. 93–98. doi: https://doi.org/10.1109/ICMEW59549.2023.00023.

[2] D. W. Otter, J. R. Medina, and J. K. Kalita, "A Survey of the Usages of Deep Learning for Natural Language Processing," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 32, no. 2, pp. 604–624, Feb. 2021, doi: https://doi.org/10.1109/TNNLS.2020.2979670.

https://doi.org/10.63876/ijtm.v4i2.137

[3] R. Xiao *et al.*, “Towards Energy-Preserving Natural Language Understanding With Spiking Neural Networks,” *IEEE/ACM Trans. Audio, Speech, Lang. Process.*, vol. 31, pp. 439–447, 2023, doi: https://doi.org/10.1109/TASLP.2022.3221011.

[4] C. Wang *et al.*, “An Interpretable and Accurate Deep-Learning Diagnosis Framework Modeled With Fully and Semi-Supervised Reciprocal Learning,” *IEEE Trans. Med. Imaging*, vol. 43, no. 1, pp. 392–404, Jan. 2024, doi: https://doi.org/10.1109/TMI.2023.3306781.

[5] Yi Shen and Jun Wang, “An Improved Algebraic Criterion for Global Exponential Stability of Recurrent Neural Networks With Time-Varying Delays,” *IEEE Trans. Neural Networks*, vol. 19, no. 3, pp. 528–531, Mar. 2008, doi: https://doi.org/10.1109/TNN.2007.911751.

[6] W. Chen, H. Zou, and Y. Zhou, “A link prediction algorithm based on convolutional neural network,” *Phys. A Stat. Mech. its Appl.*, vol. 678, p. 130922, Nov. 2025, doi: https://doi.org/10.1016/j.physa.2025.130922.

[7] C. Patra, D. Giri, T. Maitra, and B. Kundu, “A Comparative Study on Detecting Phishing URLs Leveraging Pre-trained BERT Variants,” in *2024 6th International Conference on Computational Intelligence and Networks (CINE)*, IEEE, Dec. 2024, pp. 1–6. doi: https://doi.org/10.1109/CINE63708.2024.10881521.

[8] J. Alghamdi, Y. Lin, and S. Luo, “ABERT: Adapting BERT model for efficient detection of human and AI-generated fake news,” *Int. J. Inf. Manag. Data Insights*, vol. 5, no. 2, p. 100353, Dec. 2025, doi: https://doi.org/10.1016/j.jjimei.2025.100353.

[9] S. GÜNAY, A. ÖZTÜRK, A. T. KARAHAN, M. BARINDIK, S. KOMUT, and Y. YİĞİT, “Comparing DeepSeek and GPT-4o in ECG interpretation: Is AI improving over time?,” *Hear. Lung*, Sep. 2025, doi: https://doi.org/10.1016/j.hrtlng.2025.08.007.

[10] B. Guan, X. Zhu, and S. Yuan, “A T5-based interpretable reading comprehension model with more accurate evidence training,” *Inf. Process. Manag.*, vol. 61, no. 2, p. 103584, Mar. 2024, doi: https://doi.org/10.1016/j.ipm.2023.103584.

[11] C. Zucco, “Deep Learning Methods in NLP,” in *Encyclopedia of Bioinformatics and Computational Biology*, Elsevier, 2025, pp. 190–198. doi: https://doi.org/10.1016/B978-0-323-95502-7.00249-9.

[12] H. N. Trung, V. T. Hoang, and T. H. Huong, “Transformer-based Approach for Gender Prediction using Vietnamese Names,” *Procedia Comput. Sci.*, vol. 235, pp. 2362–2369, 2024, doi: https://doi.org/10.1016/j.procs.2024.04.224.

[13] H.-V. Tran, V.-T. Bui, D.-T. Do, and V.-V. Nguyen, “Combining PhoBERT and SentiWordNet for Vietnamese Sentiment Analysis,” in *2021 13th International Conference on Knowledge and Systems Engineering (KSE)*, IEEE, Nov. 2021, pp. 1–5. doi: https://doi.org/10.1109/KSE53942.2021.9648599.

[14] T. Nguyen, V. Tran, N. Nguyen, T. Huynh, and D. Dinh, “Chatbot for E-Commerce Service Based on Rasa Framework and BERT Model,” in *2024 16th International Conference on Knowledge and System Engineering (KSE)*, IEEE, Nov. 2024, pp. 01–05. doi: https://doi.org/10.1109/KSE63888.2024.11063477.

[15] T.-K. Dao, D.-V. Nguyen, M.-V. Pham, and N.-N. Duong, “Sino-Vietnamese Text Transcription using Word Embedding Approach,” in *2024 Tenth International*

Conference on Communications and Electronics (ICCE), IEEE, Jul. 2024, pp. 392–397. doi: https://doi.org/10.1109/ICCE62051.2024.10634601.

[16] N. H. Nguyen, D. T. D. Vo, K. Van Nguyen, and N. L.-T. Nguyen, "OpenViVQA: Task, dataset, and multimodal fusion models for visual question answering in Vietnamese," *Inf. Fusion*, vol. 100, p. 101868, Dec. 2023, doi: https://doi.org/10.1016/j.inffus.2023.101868.

[17] J. Alghamdi, Y. Lin, and S. Luo, "Fake news detection in low-resource languages: A novel hybrid summarization approach," *Knowledge-Based Syst.*, vol. 296, p. 111884, Jul. 2024, doi: https://doi.org/10.1016/j.knosys.2024.111884.

[18] Song Nguyen Duc Cong, Quoc Hung Ngo, and R. Jiamthapthaksin, "State-of-the-art Vietnamese word segmentation," in *2016 2nd International Conference on Science in Information Technology (ICSITech)*, IEEE, Oct. 2016, pp. 119–124. doi: https://doi.org/10.1109/ICSITech.2016.7852619.

[19] N. T. M. Trang and M. Shcherbakov, "Vietnamese Question Answering System f rom Multilingual BERT Models to Monolingual BERT Model," in *2020 9th International Conference System Modeling and Advancement in Research Trends (SMART)*, IEEE, Dec. 2020, pp. 201–206. doi: https://doi.org/10.1109/SMART50582.2020.9337155.

[20] W. Etaiwi and B. Alhijawi, "Comparative evaluation of ChatGPT and DeepSeek across key NLP tasks: Strengths, weaknesses, and domain-specific performance," *Array*, vol. 27, p. 100478, Sep. 2025, doi: https://doi.org/10.1016/j.array.2025.100478.

[21] L. Torbarina, T. Ferkovic, L. Roguski, V. Mihelcic, B. Sarlija, and Z. Kraljevic, "Challenges and Opportunities of Using Transformer-Based Multi-Task Learning in NLP Through ML Lifecycle: A Position Paper," *Nat. Lang. Process. J.*, vol. 7, p. 100076, Jun. 2024, doi: https://doi.org/10.1016/j.nlp.2024.100076.