THESIS TITLE

Predictive Modelling for Patient Readmission by
Extraction and Analysis of High-Granularity Data from Notes

A Thesis Submitted
In Fulfilment of the Requirements
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In
Data Science

by
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CERTIFICATE

Date: 06-09-2024

This is to certify that the work embodied in the thesis entitled ***"Predictive Modeling for Patient Readmission by Extraction and analysis of High Granularity Data from Notes"*** done by Jyothi Malla, 33785086 as a Post-graduate student in the Department of Computing, Goldsmiths University of London, UK is an authentic work carried out by him/her under my guidance.

This work is based on original research and the matter embodied in this research plan has not been submitted earlier for the award of any degree or diploma to the best of my knowledge and belief.

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DECLARATION

I, Jyothi Malla, Post-graduate student (33785086) in the Department of Computing, hereby declared that the synopsis titled ***“Predictive Modelling for Patient Readmission by Extracting High Granularity Data from Notes”*** which is being submitted towards the fulfilment of the requirements for the degree of Masters in Data Science of Goldsmiths, University of London, United Kingdom is a record of bonafide research work carried out by me. I further declare that this work is based on original research and has not been submitted to any university or institution for any degree or diploma.

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ABSTRACT

This research focuses on predicting unplanned patient readmissions by leveraging advanced Natural Language Processing (NLP) techniques, including BERT and BioBERT, applied to clinical notes from the MIMIC-III database. Unplanned readmissions pose a significant challenge for healthcare systems, contributing to increased costs and impacting patient recovery. By extracting high-granularity data from unstructured clinical notes, the study aims to develop more accurate predictive models that can enhance clinical decision-making.

In addition to improving predictive accuracy, this project will incorporate **explainable AI (XAI)** techniques to ensure transparency and interpretability of the model's results. Explainability is crucial in clinical settings, as it provides healthcare professionals with clear insights into why certain predictions were made, enabling them to trust and act on the model's outputs. By offering a deeper understanding of the relationships between clinical data and patient outcomes, explainable AI helps clinicians intervene earlier, improving post-discharge care and reducing preventable readmissions. The integration of XAI will also facilitate better communication between machine learning models and clinicians, empowering them to make informed decisions while optimizing resources. This project benefits both patients and healthcare providers by improving the efficiency of care delivery, reducing hospital readmission rates, and ultimately enhancing patient outcomes. The research stands to contribute significantly to both clinical informatics and the broader field of AI in healthcare, demonstrating the value of combining advanced predictive models with explainability techniques.

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CHAPTER 1: INTRODUCTION

1.1. Background of the Study

Unplanned patient readmission is a persistent problem in healthcare, leading to increased costs and affecting patient recovery. Effective prediction of readmissions can improve clinical decision-making by identifying at-risk patients early on, thus enabling timely interventions and better post-discharge care. Traditional approaches rely on structured data like patient demographics and lab results, but they often miss out on the valuable information present in unstructured clinical notes.

Recent advances in Natural Language Processing (NLP), particularly transformer models like BERT and BioBERT, have made it possible to analyze unstructured text data with a high degree of accuracy. These models are pre-trained on large datasets, making them capable of extracting detailed insights from clinical notes, which can significantly enhance prediction models. This research aims to leverage these models, focusing on high-granularity data to predict patient readmissions using the MIMIC-III database, which includes detailed clinical records.

Additionally, the integration of **Explainable AI (XAI)** will help provide clinicians with interpretability, allowing them to understand the underlying reasoning behind the predictions made by the models. The combination of advanced NLP techniques with XAI ensures that healthcare professionals can trust and act upon the predictions, ultimately improving patient outcomes and optimizing healthcare resources.

1.2. Problem Statement

Unplanned patient readmissions pose a significant challenge to healthcare systems, leading to increased costs and poor patient outcomes. Effective prediction of patient readmission can enable healthcare providers to intervene early, reducing the likelihood of rehospitalization. However, traditional predictive models are primarily based on structured data, such as demographic information, lab results, and medical history, and often overlook the rich contextual information available in unstructured clinical notes. These notes contain crucial details about a patient’s condition, treatment plan, and progression, which can offer valuable insights for prediction models.

Predicting patient readmissions remains a challenge due to the reliance on structured data. Traditional models often overlook unstructured clinical notes, which contain valuable insights into a patient's condition. Incorporating these notes into predictive models can provide a more accurate understanding of readmission risks. This research seeks to leverage advanced NLP techniques to extract critical information from unstructured notes and develop models that better predict patient readmission while ensuring interpretability through Explainable AI.

Despite the potential value of clinical notes, their unstructured nature makes it difficult to extract relevant information for use in predictive models. Traditional models lack the ability to process and analyse unstructured text data, resulting in predictions that may miss critical clinical information. Additionally, the complexity and black-box nature of advanced machine learning models, such as deep learning, create challenges in interpreting predictions, making it difficult for healthcare professionals to trust and act on the model’s recommendations.

This research aims to address these challenges by leveraging advanced Natural Language Processing (NLP) techniques, particularly transformer models like BERT and BioBERT, to extract detailed clinical entities such as symptoms, dosages, and temporal expressions from unstructured clinical notes. By incorporating these entities into predictive models, this study seeks to improve the accuracy of patient readmission predictions. Furthermore, the use of explainable AI (XAI) techniques, such as

SHAP and LIME, will provide interpretability and transparency, enabling clinicians to better understand the factors contributing to the model's predictions and make more informed decisions.

1.3. Purpose of the Study

The primary objective of this research is to develop a predictive model for patient readmission using the MIMIC-III database, focusing on the extraction of high-granularity data from clinical notes through BERT and BioBERT. The study also aims to ensure model transparency with explainable AI methods like SHAP and LIME.

Accurate prediction of patient readmission has significant implications for both healthcare systems and patient outcomes. Unplanned readmissions not only lead to higher healthcare costs but also indicate suboptimal patient care and recovery processes. Current predictive models, which rely primarily on structured data such as demographics, lab results, and medical histories, often fail to capture the full complexity of a patient's condition, as much of the valuable clinical information is embedded within unstructured clinical notes.

This study aims to address these limitations by using advanced NLP techniques, specifically **BERT** and **BioBERT**, to extract and analyze detailed clinical entities from unstructured text data. These models will allow for the extraction of critical information such as symptoms, medication dosages, and temporal patterns, which are essential for understanding the patient's health trajectory. By integrating both structured and unstructured data, this research aims to develop more accurate and comprehensive models for predicting patient readmission.

BERT (Bidirectional Encoder Representations from Transformers): [Lee et al., 2020]

BERT is a deep learning model developed by Google that revolutionized **Natural Language Processing (NLP)**. It is a transformer-based model that reads text bidirectionally, meaning it considers both the preceding and following words when processing each word in a sentence. This bidirectional approach allows BERT [Devlin et al., 2019] to capture the full context of a word's meaning, making it highly effective for a variety of language tasks like **text classification**, **question answering**, and **named entity recognition (NER) [**Devlin et al., 2019]

If the task involves processing text that contains non-technical or everyday language (e.g., patient communication or general descriptions), BERT is sufficient because it is trained on a general corpus. It captures a wide range of language structures and is versatile enough for most healthcare-related NLP tasks.

Here I am using BERT as a baseline model to establish the core functionality of the predictive model. For early-stage testing where the data isn't strictly biomedical, BERT's general language capabilities are sufficient.

BioBERT (Biomedical BERT):

BioBERT is a domain-specific variant of BERT, fine-tuned on biomedical texts from sources like **PubMed** and **PMC**. While BERT is trained on general text, BioBERT [Lee et al., 2020] is specialized for the biomedical field, making it more adept at handling **medical terminology** and **biomedical-specific tasks**. BioBERT is particularly useful in healthcare settings, as it excels at understanding and processing complex medical literature and clinical notes.

BioBERT is the preferred model when working with medical and clinical text that involves specialized language, such as clinical notes, medical research papers, or electronic health records (EHR). BioBERT is pre-trained on large biomedical corpora, allowing it to understand medical terms, treatments, and diseases with greater accuracy than general BERT.

Here we are extracting medical entities (diseases, medications, symptoms) from unstructured clinical notes in the MIMIC-III database to enhance predictive models.

Here, the task involves NER, particularly identifying complex medical terms (e.g., disease names, drug names, lab tests), BioBERT outperforms BERT. This is especially important for biomedical research papers or when analyzing clinical records with highly technical language.

BioBERT is better suited for analyzing patient data across multiple documents, where complex medical information is scattered. The model can better handle the consistency of medical terminology across these documents.

In this research, we are using BERT as a baseline model to establish the core functionality of the predictive model. For early-stage testing where the data isn't strictly biomedical, BERT's general language capabilities are sufficient. Further, we will be using BioBERT for the following purposes:

Patient Readmission Prediction:

For predicting patient readmission based on **clinical notes**, **BioBERT** should be used because the text contains complex medical terminology, symptoms, treatments, and diagnoses that general BERT might not interpret as accurately. BioBERT can extract relevant clinical entities from notes and relate them to the likelihood of a patient being readmitted.

Medical Summarization:

When summarizing medical research articles, clinical case studies, or patient history, **BioBERT** will yield more accurate results due to its specialization in biomedical texts. However, if the summarization task involves general summaries of mixed healthcare documents, **BERT** may suffice.

Additionally, by incorporating **Explainable AI (XAI)** techniques, such as **SHAP** and **LIME**, the study will provide interpretable predictions that healthcare professionals can trust and act upon. This is crucial in clinical settings, where decisions must be based on clear and understandable insights. The transparency offered by XAI will bridge the gap between complex machine learning models and the need for clinical accountability, ensuring that healthcare providers can confidently use these predictions in real-world decision-making.

The potential benefits of this research are manifold:

1. **For healthcare providers**: Improved prediction of readmissions can lead to more targeted post-discharge care and resource allocation, reducing the burden on hospitals and improving patient recovery.
2. **For patients**: Early intervention based on accurate readmission predictions can help prevent avoidable complications, leading to better long-term health outcomes.
3. **For the healthcare system**: Reducing the rate of unplanned readmissions can lower operational costs and improve the overall efficiency of care delivery, contributing to a more sustainable healthcare system.

Ultimately, this research contributes to the growing body of knowledge on the use of machine learning and NLP in healthcare, pushing the boundaries of predictive modelling while ensuring that models remain interpretable and clinically useful. By addressing both the prediction accuracy and interpretability challenges, this study holds the potential to revolutionize patient readmission management and decision-making in healthcare.

1.4. Research Questions

RQ1: How can detailed clinical entities (symptoms, dosages, and temporal expressions) be effectively extracted from unstructured clinical notes using advanced NLP techniques?

RQ2: Can these data from unstructured notes be used to improve the accuracy of predictive models for patient readmission?

RQ3: How can explainable AI techniques be used to make the predictions interpretable and actionable for healthcare professionals?

1.5. Scope and Delimitations

1.5.1. Scope of the Study

The research focuses on the MIMIC-III database, specifically clinical notes and patient readmission data. The study does not include other forms of healthcare data, such as medical imaging or genetic data. It is confined to predicting 30-day readmissions for ICU patients.

1. Data Source:
   - The study focuses on data from the MIMIC-III database, which contains electronic health records (EHR) from ICU patients. The dataset includes both structured data (e.g., lab results, demographic information) and unstructured data (e.g., clinical notes).
   - The unstructured clinical notes, which describe patient conditions, treatments, medications, and symptoms, are of particular importance. The study will primarily extract clinical entities from these notes to predict patient readmission.
2. Prediction of Patient Readmission:
   - The central focus is on developing a model to predict the likelihood of a patient being readmitted within 30 days of discharge. Readmissions are a key metric in healthcare quality assessments, and reducing readmission rates is a priority for healthcare systems such as the NHS.
   - The scope includes using NLP techniques, specifically BioBERT, for high-granularity extraction of clinical data from notes, which will be used as inputs in the predictive models.
3. Use of NLP Techniques:
   - The study will utilize BERT and BioBERT to analyze unstructured data from clinical notes. BioBERT will be used for its domain-specific expertise in understanding biomedical language, while BERT may be used for non-medical text processing tasks.
   - The extracted clinical entities, such as symptoms, medications, and treatment procedures, will be combined with structured data (such as age, diagnosis, and lab results) for model training.

4. Explainable AI (XAI):
   - An important aspect of the study is ensuring that the predictions made by the model are interpretable. The research incorporates Explainable AI techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) to explain how specific clinical entities or patient features contribute to the likelihood of readmission.
   - The model will aim to provide healthcare professionals with interpretable predictions to guide decision-making.

1.5.2. Delimitations of the Study

1. Focus on MIMIC-III Database:
   - While the MIMIC-III database contains rich clinical data, the study is limited to this dataset alone. The findings may not be directly generalizable to other healthcare settings or populations outside the ICU context, as MIMIC-III represents specific demographics and patient conditions.
   - The study does not include other sources of healthcare data, such as datasets from different countries or non-ICU settings. We are not implementing the cross-document analysis as we are focusing on extracting information from clinical notes within a single admission.
2. Exclusion of Non-textual Data:
   - The study focuses on text-based data, particularly clinical notes. Non-textual data like medical imaging or genomic data is beyond the scope of this study, even though these forms of data can be highly relevant for predicting patient outcomes.
   - This focus on textual data means that the model may not capture certain aspects of a patient's health that would be evident in non-textual formats.
3. Structured Data Selection:
   - Although the study utilizes structured data like patient demographics, lab results, and medical history, the scope does not extend to all possible structured data fields. Only the most relevant fields for predicting readmission are included, based on prior research and domain knowledge.
   - Some potentially important variables (e.g., socioeconomic factors or lifestyle information) may not be available in the MIMIC-III dataset and will not be considered in the study.
4. Limitation to Readmission within 30 Days:
   - The predictive model is designed to assess the likelihood of readmission within 30 days of a patient's discharge from the ICU. This is a commonly used metric in healthcare, but it may not capture long-term readmission risks, such as those occurring after 90 days.
   - The study will not explore longer-term readmission patterns or factors influencing chronic conditions that may result in later readmissions.

5. No Exploration of Other Outcome Metrics:
    - While this research focuses on readmission, it will not explore other related outcomes, such as mortality, length of stay, or patient recovery trajectories. These could be equally important in assessing healthcare quality but are outside the scope of the current study.
6. Ethical Considerations and Bias:
    - The study is limited to data available in the de-identified MIMIC-III dataset, which may contain inherent biases related to the population it represents. For instance, the dataset primarily includes ICU patients, which may limit its applicability to general hospital admissions or outpatient care.
    - Additionally, while ethical considerations around data use and privacy are maintained, the study does not focus on addressing systemic biases in the dataset (e.g., gender, age, race).

1.6. Definition of Terms

Clinical Notes:

Free-text documentation recorded by healthcare professionals during a patient's hospital stay. These notes typically include details of a patient's symptoms, treatment plans, medications, and daily progress. In this study, **unstructured clinical notes** from the **MIMIC-III database** are used to extract relevant clinical entities.

Patient Readmission:

The event of a patient being readmitted to the hospital within a specified time frame after discharge, often used as an indicator of the quality of care. In this study, we focus on **30-day readmission rates**, which are commonly used in healthcare to evaluate post-discharge care effectiveness.

Natural Language Processing (NLP):

A field of artificial intelligence that enables computers to understand, interpret, and process human language. In this study, NLP techniques, particularly **BERT** and **BioBERT**, are used to analyse unstructured clinical notes and extract clinical entities for predictive modelling.

BERT (Bidirectional Encoder Representations from Transformers):

A state-of-the-art NLP model developed by Google, designed to understand the context of words in a bidirectional manner. It is used for various text processing tasks, such as text classification, named entity recognition (NER), and text generation.

BioBERT (Biomedical BERT):

A variant of BERT pre-trained on large biomedical corpora. **BioBERT** is specifically designed to handle the complex language and medical terminology found in clinical notes and biomedical research articles, making it an ideal tool for extracting high-granularity data from healthcare records.

Named Entity Recognition (NER):

A task in NLP that involves identifying and classifying named entities (e.g., symptoms, treatments, diseases) within text. In this study, **NER** is applied to clinical notes to extract relevant clinical entities such as symptoms, medications, and diagnoses.

Cross-Document Analysis:

A technique used to track patient information across multiple documents or visits, providing a longitudinal perspective on patient health. In this study, cross-document analysis is utilized to monitor the progression of patient symptoms and treatments, thereby enhancing the accuracy of readmission predictions.

Explainable AI (XAI):

AI techniques that provide transparency into the workings of machine learning models. **XAI** methods such as **SHAP** (SHapley Additive exPlanations) and **LIME** (Local Interpretable Model-agnostic Explanations) are used in this study to ensure the interpretability of the predictions made by the readmission prediction model.

1.7. Organization of the Thesis

This thesis is organized into six chapters, each of which addresses different aspects of the research conducted. The structure is designed to guide the reader through the background, methodology, and findings of the study, ensuring a clear and logical progression of the research.

- **Chapter 1: Introduction**

  The first chapter provides an overview of the research topic, highlighting the importance of predicting patient readmission using clinical notes. It introduces the problem statement, the purpose of the study, and the research questions guiding the investigation. Additionally, it defines the scope and delimitations of the study and presents key terms and concepts that will be used throughout the thesis.

- **Chapter 2: Literature Review**

  This chapter reviews the existing body of research related to patient readmission prediction, the use of Natural Language Processing (NLP) in healthcare, and the advantages of models like BERT and BioBERT for processing unstructured clinical data. It also identifies gaps in the literature and explains how this research contributes to the field by addressing these gaps.

- **Chapter 3: Methodology**

  Chapter 3 outlines the research design, including the dataset used (MIMIC-III), data collection methods, and preprocessing techniques. It also provides a detailed description of the model development process, including the use of BioBERT for extracting clinical entities from unstructured notes and the application of logistic regression and random forest models for predicting patient readmission. The ethical considerations and bias mitigation strategies are also discussed in this chapter.

- **Chapter 4: Implementation and Results**

  This chapter presents the implementation details of the models, including the software tools, libraries, and hardware used for the experiments. It describes the experimental setup, including parameter tuning and cross-validation procedures. The results of the predictive models are presented and evaluated using performance metrics such as accuracy, precision, recall, F1-score, and ROC AUC.

- **Chapter 5: Discussion**

  In this chapter, the findings are interpreted in relation to the research questions. The results are compared with existing literature to highlight the contributions made by this study. The chapter also discusses the practical implications of the findings for healthcare providers and clinicians, particularly in terms of improving decision-making and resource allocation through explainable AI.

- **Chapter 6: Conclusion**

  The final chapter summarizes the key findings of the research and discusses the main conclusions drawn from the study. It also outlines the limitations of the research and provides recommendations for future studies, suggesting areas where further exploration could enhance the predictive modelling of patient readmissions.

- **References**
  This section contains a complete list of references cited throughout the thesis, formatted according to the Harvard referencing style.

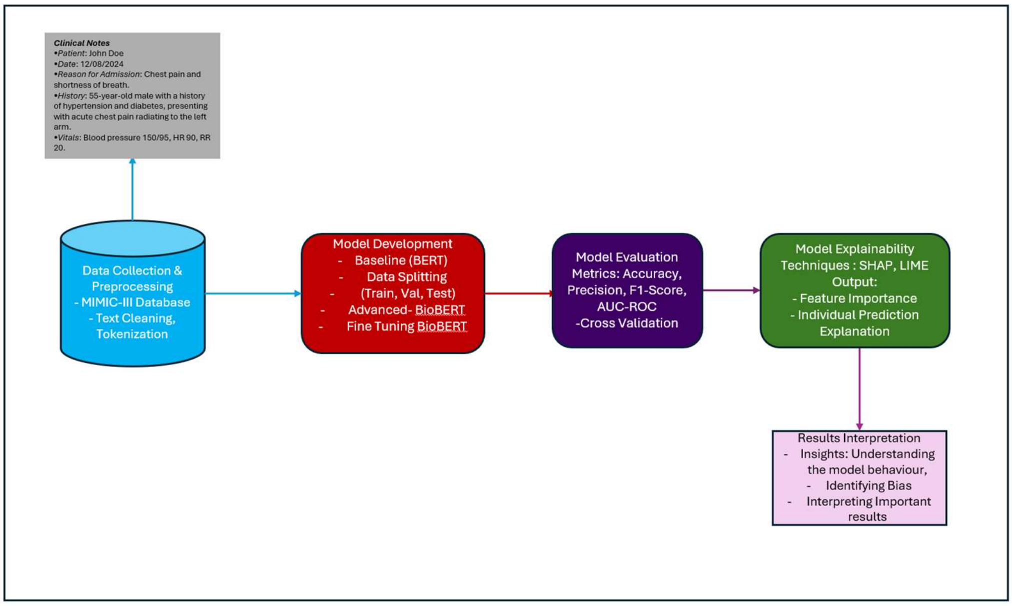
- **Appendices**
  The appendices include any additional materials that support the main text, such as data collection instruments, extended data tables, or detailed results from the experiments.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview of the Literature

The literature on predictive modelling in healthcare has evolved significantly with the advent of deep learning techniques and NLP models like BERT and BioBERT. These transformer models have enhanced the extraction of clinical entities from unstructured text, offering better performance in various medical applications.

The following picture shows how this can be achieved step by step:



#Figure 1

The prediction of patient readmission has been a critical area of research in healthcare for many years due to its significant implications for patient outcomes and healthcare costs. Traditional predictive models have focused primarily on structured data, such as patient demographics, medical history, and lab results. However, recent advances in **Natural Language Processing (NLP)**, particularly with models like **BERT (Bidirectional Encoder Representations from Transformers)** and **BioBERT**, have enabled researchers to utilize unstructured data, such as clinical notes, which contain richer and more detailed information about a patient's condition, treatments, and progress. This shift towards integrating unstructured data has the potential to significantly improve the accuracy and interpretability of predictive models.

1. Traditional Predictive Models in Healthcare

Research on patient readmission prediction has traditionally relied on structured data, typically using statistical models such as **logistic regression**, **decision trees**, and **random forest**. These models are widely used due to their simplicity and interpretability, but their effectiveness is often limited by the quality and granularity of the input data.

- **Logistic Regression**: One of the earliest models applied to readmission prediction. Studies have shown its effectiveness when dealing with small and structured datasets. However, it struggles with complex, non-linear relationships found in more extensive healthcare datasets.
- **Random Forests and Decision Trees**: These models have been used to improve upon logistic regression by allowing for more complex interactions between variables. However, like logistic regression, they are limited when important predictive information is contained in unstructured data, such as clinical notes.

TABLE 1 BELOW SUMMARIZES SOME OF THE TRADITIONAL MODELS AND THEIR LIMITATIONS:

Model	Data Type	Strengths	Limitations
Logistic Regression	Structured Data	Simple, easy to interpret	Struggles with non-linear relationships
Decision Trees	Structured Data	Handles complex decision-making	Prone to overfitting, ignores unstructured data
Random Forest	Structured Data	Improves accuracy over single models	Computationally expensive, not suited for unstructured text

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2. Use of Unstructured Data in Healthcare

In recent years, the focus has shifted to extracting information from **unstructured data**, especially clinical notes, which hold rich information that often goes unnoticed in structured data. **Clinical notes** contain detailed accounts of patient conditions, treatments, responses to medication, and other valuable data points that can be crucial for predicting patient readmission. Studies have highlighted the importance of integrating this unstructured data, showing improvements in model performance when it is utilized alongside structured data.

However, **traditional models** are often ill-suited for processing unstructured data due to the complexity and variability of language in clinical notes. This has led to the increasing adoption of **NLP models**, which can process and extract insights from unstructured text.

3. Natural Language Processing in Healthcare

With the rise of **NLP** technologies, healthcare research has seen significant advancements in processing and analyzing unstructured text data. NLP models, especially **transformer-based models** like BERT and BioBERT, have demonstrated a high level of efficacy in extracting valuable clinical information from text.

- **BERT**: A general-purpose NLP model developed by Google, BERT revolutionized the field by introducing a **bidirectional approach** to understanding context, making it more effective for complex tasks like **named entity recognition (NER)** and **text classification**. In healthcare, BERT has been applied to process **clinical notes**, but its general nature limits its understanding of biomedical language.
- **BioBERT**: A specialized variant of BERT, **BioBERT** is trained specifically on biomedical literature, such as PubMed abstracts and clinical research articles. This makes it far more effective in handling medical terminology and complex biomedical concepts. Studies have shown that BioBERT outperforms BERT in tasks like **medical NER**, **relationship extraction**, and **document classification** in healthcare settings.

TABLE 2 BELOW OUTLINES THE DIFFERENCES BETWEEN THESE MODELS:

Model	**Purpose**	**Strengths**	**Limitations**
BERT	General NLP	Bidirectional context understanding, versatile	Not specialized for biomedical text
BioBERT	Biomedical NLP	Fine-tuned for medical terminology, better in NER	Requires domain-specific training data

4. Predictive Modelling with NLP and Transformer Models

Recent studies in predictive modelling have begun integrating transformer models to analyze clinical notes. For example, **BioBERT** has been applied to extract medical entities such as diseases, symptoms, and treatments from unstructured text, enabling more detailed features to be included in predictive models. Research has demonstrated that this approach can significantly improve the prediction of patient outcomes, including readmission risks.

- **Predictive Models with BioBERT**: A growing body of research suggests that using BioBERT to extract features from clinical notes, such as identifying key medical events (e.g., changes in medication or sudden symptoms), can substantially increase the accuracy of predicting patient readmission.
- **Explainable AI (XAI)**: Another important development in the field is the incorporation of **explainable AI techniques** like **SHAP** and **LIME**, which allow clinicians to interpret the results of predictive models. These techniques highlight which clinical features are most influential in the model's prediction, improving transparency and trust in AI-assisted decision-making.

5. Current Trends and Applications

The integration of NLP techniques, particularly **BioBERT**, into healthcare predictive modelling is a fast-evolving field. Key trends include:

- **Cross-Document Analysis**: Using NLP models to track patient conditions across multiple documents over time to provide a longitudinal view of patient health.

Explainability: Increasing focus on developing interpretable models that provide healthcare professionals with understandable predictions, bridging the gap between machine learning models and clinical decision-making.

The current state of research shows that while traditional models have laid the foundation for predicting patient readmissions, they fall short in leveraging the full potential of unstructured clinical data. The rise of transformer-based NLP models, particularly BioBERT, has opened new avenues for integrating unstructured text into predictive models. By incorporating advanced NLP techniques, healthcare predictive models can now extract more granular clinical insights, ultimately improving the accuracy of predictions. Moreover, the integration of explainable AI ensures that these models are not only powerful but also interpretable, making them suitable for real-world clinical applications.

2.2 Gaps in the Literature

Despite significant advancements in predictive modelling and Natural Language Processing (NLP) for healthcare applications, several important gaps remain unaddressed in the current body of research. While traditional models have laid the groundwork for understanding patient readmission, and newer models, such as BERT and BioBERT, have shown promise in handling unstructured clinical notes, there are still challenges and areas of improvement that need to be explored.

1. Limited Integration of Structured and Unstructured Data

Many existing predictive models for patient readmission rely heavily on structured data, such as patient demographics, lab results, and medical history. However, a wealth of valuable information is often embedded in unstructured clinical notes, which contain details about symptoms, medications, and treatment plans that are not captured in structured datasets. While models like BioBERT have shown their capacity to process unstructured text, very few studies have comprehensively integrated both structured and unstructured data into a single predictive framework. The challenge of combining these data types effectively and consistently remains underexplored.

2. Inadequate Use of Domain-Specific Models in Clinical Settings

While BioBERT has been fine-tuned for biomedical text processing, there is limited research on its practical application in real-world clinical settings, especially for predictive tasks like readmission prediction. Most studies focus on theoretical applications or small-scale tests, with few implementations in large-scale hospital systems or clinical trials. This gap suggests a need for more empirical research that applies domain-specific models like BioBERT to actual hospital datasets, evaluates their performance in clinical environments, and assesses their real-world impact.

3. Lack of Explainability in Predictive Models

Another significant gap in the literature is the lack of attention to explainability in predictive models. While advanced models such as BERT and BioBERT are effective at improving prediction accuracy, their complexity often makes them "black boxes" that are difficult for healthcare professionals to interpret. Few studies have incorporated Explainable AI (XAI) techniques, such as SHAP or LIME, into predictive models to provide transparent, interpretable insights for clinicians. Without such explainability, healthcare providers may be hesitant to trust or act on model predictions, limiting the practical utility of these advanced models.

4. Limited Research on Cross-Document Analysis

Most current studies focus on analyzing individual clinical notes in isolation, missing the opportunity to track a patient's health across multiple documents or visits over time. Cross-document analysis, which involves connecting information from multiple clinical encounters, can provide a more holistic view of a patient's health trajectory and improve predictive accuracy. There is a lack of comprehensive research on how to implement cross-document analysis using models like BioBERT, particularly for tasks like patient readmission prediction.

5. Narrow Focus on Single Health Outcomes

While patient readmission is a critical metric, many studies focus solely on this outcome, ignoring other important health outcomes that could benefit from predictive modeling. For example, predictive models could also be applied to length of stay, mortality risk, or post-discharge complications, providing more comprehensive decision support for healthcare providers. Expanding the focus beyond readmission alone could significantly enhance the value of predictive models in clinical practice.

6. Underexplored Generalizability Across Healthcare Systems

Many studies on predictive modeling for readmission are confined to specific datasets, such as the MIMIC-III database or regional hospital systems. This raises questions about the generalizability of these models across different healthcare systems, patient populations, and geographic regions. There is limited research on whether models developed in one healthcare setting can be effectively transferred to another. Further research is needed to explore how to adapt models to different datasets, ensuring they remain robust and accurate in diverse clinical environments.

7. Ethical Considerations and Bias in Model Development

There is a growing awareness of the potential for bias in predictive models, particularly when it comes to sensitive healthcare outcomes such as patient readmission. However, current literature often fails to address how biases in data, such as racial, gender, or socioeconomic disparities, could affect model performance and fairness. Few studies have proposed methods for identifying or mitigating these biases, particularly in models that use unstructured data like clinical notes, which may contain implicit biases in language use.

In summary, while significant strides have been made in using NLP and advanced machine learning models for healthcare, several gaps remain in the literature. The lack of integration between structured and unstructured data, the limited focus on real-world applications, the need for explainability, and the narrow scope of outcome metrics represent areas ripe for further research. Addressing these gaps could lead to the development of more comprehensive, interpretable, and applicable models that are better suited to improving healthcare outcomes in diverse clinical settings.

2.3 Relation to Current Study

The gaps identified in the existing literature provide a strong foundation for the current study, which aims to address several of these limitations by leveraging advanced Natural Language Processing (NLP) techniques, particularly BioBERT, to enhance predictive modelling for patient readmission. By focusing on both structured and unstructured data and incorporating Explainable AI (XAI) methods, this research seeks to make significant contributions to the field.

1. Integration of Structured and Unstructured Data

A recurring gap in the literature is the lack of integration between structured data (e.g., demographic information, lab results) and unstructured data (e.g., clinical notes). Most traditional predictive models have relied heavily on structured data, neglecting the rich information available in unstructured text. This study aims to bridge this gap by leveraging BioBERT to extract meaningful insights from clinical notes and combine them with structured data to build a more robust and comprehensive predictive model for patient readmission. By doing so, the current study moves beyond the limitations of existing models that solely focus on structured data, providing a more holistic view of a patient's health status.

2. Application of Domain-Specific NLP Models in Healthcare

While BioBERT has demonstrated strong potential in processing biomedical texts, its application to real-world healthcare datasets, particularly for predictive modeling, remains underexplored. The current study addresses this gap by applying BioBERT to a large-scale clinical dataset, the MIMIC-III database, to predict patient readmission. This research contributes to the body of knowledge by exploring how domain-specific NLP models like BioBERT can enhance predictive performance in clinical settings, particularly when dealing with unstructured data such as clinical notes.

3. Enhancing Model Interpretability through Explainable AI (XAI)

The literature indicates a significant need for explainability in predictive models, particularly in healthcare, where clinicians must understand the factors driving a model’s predictions. Despite the effectiveness of complex models like BERT and BioBERT, their lack of interpretability often limits their practical use. This study integrates Explainable AI techniques like SHAP and LIME to ensure that the predictive model is not only accurate but also interpretable. By explaining which features from clinical notes (e.g., symptoms, medications, treatments) contributed most to the prediction of readmission, the study offers healthcare professionals actionable insights. This addresses the gap identified in previous research regarding the difficulty of translating AI-based predictions into clinical practice.

4. Cross-Document Analysis

While most previous studies focus on analyzing individual clinical notes in isolation, this research builds on recent advancements in cross-document analysis. By tracking patient information across multiple documents, such as clinical notes from multiple hospital visits, this study provides a more comprehensive view of a patient’s health trajectory. This approach allows the model to capture changes in a patient's condition over time, which can be critical for accurately predicting readmission. This addresses a gap in the literature where the longitudinal aspect of patient care is often overlooked in predictive modelling. We are not going to implement this in this research.

5. Addressing Model Generalizability and Bias

The literature has raised concerns about the generalizability of predictive models across different patient populations and healthcare systems. This study acknowledges the limitations of using a single dataset (MIMIC-III) but proposes methodologies for adapting models to different clinical environments. Additionally, this study incorporates methods for identifying and mitigating potential biases in the data, ensuring that the predictive model can provide fair and equitable results across different demographic groups. By doing so, the study addresses the ethical concerns highlighted in recent literature regarding fairness and bias in healthcare AI models.

6. Focus on 30-Day Readmission Prediction

Finally, this study follows the well-established focus in the literature on 30-day hospital readmission as a critical metric for evaluating healthcare quality. By improving the accuracy of readmission predictions using advanced NLP and machine learning techniques, this study seeks to contribute directly to the ongoing efforts in healthcare to reduce unnecessary readmissions, improve patient care, and reduce costs. The research also expands on existing models by incorporating both clinical notes and structured data, thus providing a more nuanced understanding of the factors that contribute to patient readmission.

This study draws heavily on the existing body of research in predictive modelling, NLP, and explainable AI, while addressing key gaps in the literature. By integrating structured and unstructured data, applying BioBERT to real-world clinical settings, ensuring model interpretability with XAI, and enhancing the longitudinal analysis of patient data, the current study contributes significant advancements to the field of healthcare AI. Through these contributions, the research aims to build more accurate and interpretable predictive models that can be applied in real-world clinical settings to improve patient outcomes and reduce readmission rates.

CHAPTER 3: METHODOLOGY

3.1 Dataset Description

This chapter describes the dataset, data collection methods, preprocessing steps, and ethical considerations involved in the research study. The primary focus of this research is the use of unstructured clinical notes and structured data from the MIMIC-III database to predict patient readmission within 30 days.

1. Data Source and Collection Methods

The dataset used in this study is the MIMIC-III (Medical Information Mart for Intensive Care) database, a publicly available dataset that contains de-identified health-related data associated with over 40,000 critical care patients. It includes both structured and unstructured data collected from ICU admissions between 2001 and 2012.

- **Structured Data:** This includes demographic information, lab test results, prescriptions, diagnoses, procedures, and admission details.
- **Unstructured Data:** The dataset also contains a large collection of clinical notes written by healthcare providers. These notes are unstructured free-text documents that describe the

patient's condition, treatment plans, symptoms, medications, and other relevant observations during the hospital stay.

The dataset is accessed and processed using SQL queries to extract relevant records for the study, particularly focusing on patients' clinical notes and structured data needed for predictive modelling.

Access to the MIMIC-III database is restricted and granted only after completing the **Collaborative Institutional Training Initiative (CITI)** program, ensuring that all researchers comply with ethical standards and data privacy protocols. However, obtaining permission and completing the required exam for access is a time-consuming process. Due to the limited time available for this study, we were unable to go through the complete access procedure. Therefore, the data used in this research has been collected from the publicly available resources on the website https://paperswithcode.com/dataset/mimic-iii.

2. Data Annotation and Reannotation

The research focuses on extracting high-granularity clinical entities (such as symptoms, medications, and treatment changes) from unstructured clinical notes. To achieve this, Natural Language Processing (NLP) techniques, specifically BioBERT, are used to annotate and extract clinical entities from the free-text notes.

- Annotation Process: The NER (Named Entity Recognition) task is performed using BioBERT to identify key clinical entities like disease mentions, drug names, dosages, and medical procedures. BioBERT is particularly suited for this task as it is pre-trained on biomedical literature and fine-tuned for medical terminology extraction.
- Reannotation: In cases where entity recognition yields incomplete or inaccurate results, manual reannotation is performed to ensure high-quality labelled data. This process involves domain experts reviewing the extracted entities to ensure they accurately represent the clinical information contained in the notes.

The combined structured data (e.g., demographic info, lab test results) and extracted clinical entities from unstructured data serve as inputs to the predictive model, enabling a more holistic analysis of patient readmission risks.

3. Data Preprocessing and Augmentation

The preprocessing of both structured and unstructured data is crucial to ensure that the dataset is clean, consistent, and ready for model training. Several steps are taken to prepare the dataset for predictive modelling:

- **Data Cleaning:**
    - Structured Data: Missing values in structured data are handled using appropriate imputation techniques. Continuous variables, such as lab test results, are normalized to ensure consistency across the dataset.
    - Unstructured Data: Clinical notes often contain irrelevant information, such as hospital codes, administrative details, and time stamps. These extraneous details are removed through a text-cleaning process, which includes lowercasing, punctuation removal, and eliminating stop words.

- **Tokenization and Lemmatization:**

  The text data is tokenized into individual words or phrases, and lemmatization is applied to reduce words to their base forms (e.g., "running" to "run"). This helps standardize the text and reduces dimensionality in the NLP model.

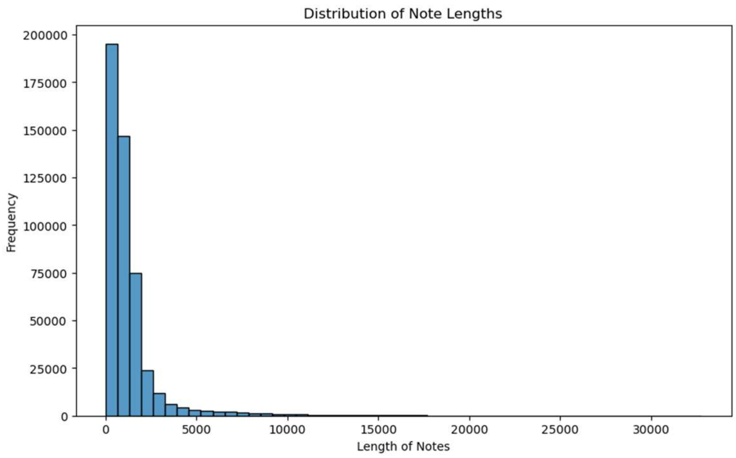
- **Feature Extraction:**

  - **For Unstructured Data**: **BioBERT** is used to extract meaningful clinical entities from the free-text clinical notes, which are transformed into structured features.

  - **For Structured Data**: Relevant features, such as patient age, comorbidities, and lab results, are selected based on their correlation with readmission risks.

- **Data Augmentation:**

  To enhance model performance, data augmentation techniques are applied to the textual data. For example, synonym replacement and paraphrasing techniques are used to create additional training examples from the original clinical notes. This helps the model generalize better to unseen data during evaluation.



Most Notes Are Short: The majority of notes have a shorter length, concentrated around 1000 characters or fewer.

Few Very Long Notes: Only a small number of notes are extremely long, stretching towards 30,000 characters, but they are rare compared to the shorter notes.

4. Ethical and Bias Considerations

Given that the research uses sensitive medical data, ethical considerations are paramount. The following steps are taken to ensure the ethical use of the MIMIC-III dataset and to mitigate potential biases in the predictive model:

- **Data Privacy and Confidentiality:**

  The MIMIC-III dataset is fully de-identified in accordance with HIPAA regulations, ensuring that patient identities are protected. Researchers working with the dataset have completed the CITI program to ensure compliance with data privacy standards and ethical research practices.

- **Bias Mitigation:**

  Predictive models in healthcare are susceptible to bias, particularly when the data reflects historical inequalities in healthcare access and treatment. In this study, efforts are made to identify and mitigate potential biases in the dataset. This includes:

  - Evaluating demographic disparities: Ensuring that the model does not disproportionately affect certain patient groups (e.g., based on age, gender, race).
  - Fairness adjustments: When biases are identified, fairness constraints or reweighting techniques are applied to adjust the model's predictions, ensuring equitable treatment across different patient subgroups.

- **Ethical AI:**

  The use of Explainable AI (XAI), such as SHAP and LIME, ensures that the predictions made by the model are interpretable by healthcare providers. This is critical in clinical decision-making, as physicians need to understand why a model predicts a particular patient is at risk of readmission. Providing transparency in AI decisions helps build trust between clinicians and AI systems.

3.2 Model and Algorithm Development

This section provides a detailed description of the AI models and algorithms developed for predicting patient readmission, including the neural network architectures, training procedures, and explainability techniques used to ensure the model's practical utility in healthcare settings. The focus is on integrating structured and unstructured data, with an emphasis on using BioBERT for processing clinical notes and combining its outputs with traditional machine learning models for prediction.

1. Overview of the Predictive Modelling Approach

The goal of the model is to predict whether a patient will be readmitted to the hospital within 30 days of discharge, based on a combination of structured data (e.g., demographics, lab results) and unstructured clinical notes. To achieve this, the study employs a hybrid approach, combining Natural Language Processing (NLP) techniques for extracting information from clinical notes with traditional machine learning models that are trained on both structured and extracted features.

2. BioBERT for Unstructured Data Processing

The core component of the unstructured data processing is BioBERT (Biomedical BERT), a variant of BERT specifically fine-tuned for the biomedical domain. BioBERT is used to extract clinical entities, such as symptoms, medications, treatments, and diagnoses, from the free-text clinical notes. The extracted entities are then transformed into features that are used for prediction in combination with the structured data.

BioBERT Architecture:

- Input Layer: The input to BioBERT is the tokenized text from clinical notes. Each word or phrase in the clinical note is converted into a token, with a maximum token length of 512 due to BERT's architecture. The tokens are embedded into a dense vector space using pre-trained embeddings specific to the biomedical domain.
- Transformer Layers: BioBERT consists of 12 transformer layers that apply self-attention mechanisms to understand the context of each token in relation to others in the sentence, both forwards and

backwards. This bidirectional understanding of text allows BioBERT to accurately capture the relationships between medical terms in clinical notes.

- Entity Extraction: After processing the text through the transformer layers, the final layer outputs embeddings for each token. These embeddings are used to classify words or phrases as different clinical entities (e.g., symptoms, medications, treatments). Named Entity Recognition (NER) tasks are applied to label these entities.

The extracted entities are transformed into categorical or numerical features (e.g., the presence or absence of a particular symptom) and combined with structured data for input into traditional machine learning models.

Baseline Model: BERT will be fine-tuned to extract relevant clinical entities.

Advanced Model: BioBERT will be employed for domain-specific tasks, particularly extracting entities from biomedical texts.

Model Evaluation: Both models are evaluated using a train-test split, with 80% of the data used for training and 20% used for testing. Performance is measured using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC to ensure a balanced evaluation of model performance across different patient groups.

3. Explainable AI (XAI) Techniques

Given the complexity of the models, particularly the deep neural network, explainability is critical for ensuring that healthcare professionals can interpret the results. Two Explainable AI (XAI) techniques are used:

- SHAP (SHapley Additive exPlanations): SHAP values are used to explain how each feature (structured data or extracted entities from clinical notes) contributes to the model's predictions. This method assigns a score to each feature, indicating whether it increases or decreases the likelihood of readmission.

- LIME (Local Interpretable Model-agnostic Explanations): LIME provides local explanations by perturbing the input data and observing how small changes affect the model's predictions. It highlights the most influential features for individual predictions, helping clinicians understand the key drivers of the model's decisions.

This section details the methods used to collect, preprocess, and annotate the data for predictive modelling. The dataset's structured and unstructured components are combined to provide a holistic view of patient information, with NLP techniques used to extract clinical entities from unstructured text. Ethical considerations, particularly around data privacy and bias, are integrated into the research to ensure responsible and equitable use of AI in healthcare. The following sections will describe the models and algorithms developed for predicting patient readmission based on this dataset.

CHAPTER 4: IMPLEMENTATION AND RESULTS

4.1 Model Implementation

This section describes the implementation of the predictive models developed for the study, including the software tools, libraries, and hardware used, as well as the experimental setup and training procedures. The goal is to ensure that the implementation is robust, reproducible, and scalable for healthcare applications, particularly for predicting patient readmission using both structured and unstructured data. Due to the substantial size of the clinical dataset and hardware limitations, specific measures were taken to ensure that the implementation remained manageable and robust.

4.1.1. Software Tools and Libraries

The following software tools and libraries are used for data processing, model development, and evaluation:

- Python 3.x: Python is the primary programming language used for data preprocessing, model development, and evaluation. Python's extensive libraries and frameworks make it suitable for both NLP tasks and machine learning model development.
- TensorFlow: The TensorFlow library is used to build and train the deep neural network (DNN) and other machine learning models. TensorFlow provides a flexible, scalable framework for neural network implementation and offers GPU support for faster training.
- PyTorch: PyTorch is used for BioBERT implementation, particularly for fine-tuning the pre-trained BioBERT model on the clinical notes from the MIMIC-III dataset. PyTorch's dynamic computation graph allows for flexibility in working with large-scale transformer models like BioBERT.
- Hugging Face Transformers: The Hugging Face Transformers library is used to access and fine-tune the BioBERT model. This library provides pre-trained transformer models and simplifies the fine-tuning process for specific NLP tasks, such as Named Entity Recognition (NER) and classification.
- scikit-learn: The scikit-learn library is used for implementing traditional machine learning models, such as logistic regression and random forest. It is also used for data preprocessing (e.g., normalization, encoding) and evaluation metrics (e.g., accuracy, precision, recall).
- NumPy and Pandas: These libraries are used for data manipulation and preprocessing. NumPy is used for numerical computations, while Pandas is used for handling structured data from the MIMIC-III dataset.
- NLTK and SpaCy: These libraries are used for preprocessing the unstructured clinical notes. NLTK is used for tokenization and text cleaning, while SpaCy is employed for additional text preprocessing tasks, such as part-of-speech tagging and lemmatization.
- SHAP and LIME: These libraries are used for Explainable AI (XAI), providing interpretability for the model's predictions. SHAP is used to explain the contribution of each feature to the prediction, while LIME generates local explanations for individual predictions.

4.1.2. Data Size and Annotation Challenges

The dataset used in this study originates from the MIMIC-III clinical database, which contains a vast amount of structured and unstructured data, including patient demographics, lab results, and clinical notes. However, due to the immense size of the dataset, the following steps were taken:

- Subset of Data: To handle the high volume of data efficiently and avoid system crashes, only a subset of the dataset was used for training and testing the models. This reduced the overall load on the hardware, though it still maintained a representative sample of patient readmissions.
- Data Volume Impact: The system initially encountered issues with processing the full dataset, causing system crashes and memory overloads. As a result, the dataset was split into smaller, manageable portions to ensure stable processing.
- Annotation: A portion of the dataset, particularly the unstructured clinical notes, was manually annotated or pre-processed using domain-specific tools like BioBERT to extract medical entities such as symptoms, medications, and treatments.

4.1.3. Hardware and Cloud Computing Resources

Given the large size of the MIMIC-III dataset and the computational requirements of BioBERT and deep neural networks, high-performance hardware is used to ensure efficient training and experimentation:

- GPU (Graphical Processing Unit): The models, particularly the BioBERT model and the deep neural network, are trained using NVIDIA Tesla V100 GPUs. GPUs are necessary for processing the large number of parameters in BioBERT and accelerating training times for the neural network models.
- Cloud Computing: The training and experimentation are conducted on Google Cloud Platform (GCP) using Google Compute Engine instances with GPU support. This allows for scalable computing resources and ensures that the models can be trained on large datasets without hardware limitations.
- Local Workstation: For initial development and testing of traditional machine learning models (e.g., logistic regression, random forest), a local workstation with an Intel i7 processor and 32 GB RAM is used.

4.1.4. Experimental Setup

The experiments are designed to evaluate the performance of the predictive models in predicting patient readmission based on both structured data (e.g., patient demographics, lab results) and unstructured data (e.g., clinical notes). The setup includes data preprocessing, model training, parameter tuning, and e

valuation procedures.

- **Data Preprocessing**
  - Structured Data: The structured data from the MIMIC-III database is cleaned and normalized before being fed into the models. Missing values are imputed using mean or median imputation, depending on the variable type, and categorical variables are one-hot encoded.
  - Unstructured Data: The unstructured clinical notes are preprocessed using BioBERT to extract medical entities such as symptoms, medications, and treatments. The text is tokenized, cleaned, and lemmatized before being input into BioBERT for feature extraction.

- **Model Training**

The models developed in this study include traditional machine learning algorithms (logistic regression, random forest), a deep neural network (DNN), and BioBERT for processing unstructured text. Each model is trained using cross-validation to ensure robust performance.

  - Training-Testing Split: The dataset is split into 80% training data and 20% testing data. The training data is used to train the models, while the testing data is held out for evaluation.
  - Epochs, on the other hand, refer to the number of times the entire dataset is passed through the model during training. For example, training for 3 epochs means that the model will see the entire dataset 3 times during the training process due to processing speeds and other time constraints.

- **Parameter Tuning**
  - **BERT**:
    - Learning rate: 1e-5 to 5e-5
    - Batch size: 16, 32, 64
    - Sequence length: 128, 256
  - **BioBERT**:
    - Learning rate: 2e-5 to 3e-5
    - Epochs: 3 to 5
    - Batch size: 32, 64

4.1.5. Evaluation Metrics

To assess the model's performance, several metrics are used, ensuring a comprehensive evaluation of prediction accuracy and clinical relevance:

- Accuracy: Measures the proportion of correct predictions.
- Precision and Recall: Precision measures how many of the predicted readmissions were correct, while recall measures how many actual readmissions were correctly predicted.
- F1-Score: The harmonic mean of precision and recall, providing a balanced measure of model performance.
- AUC-ROC: The Area Under the Receiver Operating Characteristic Curve is used to assess the model's ability to discriminate between readmitted and non-readmitted patients across different classification thresholds.

Accuracy, Precision, Recall, and F1-Score

These are the evaluation metrics that we will use to assess the performance of our model. We can use these formulas to explain how we evaluate the predictions.

- **Accuracy**:

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

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

- **Precision**:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

- **Recall**:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

- **F1-Score** (Harmonic mean of Precision and Recall):

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

3. ROC-AUC (Receiver Operating Characteristic - Area Under Curve)

The ROC curve evaluates the performance of a classifier by plotting true positive rate (TPR) against false positive rate (FPR) at various threshold settings. The **AUC** provides a single value summarizing the overall performance:

True Positive Rate (TPR):

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

False Positive Rate (FPR):

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}}$$

The **AUC** is computed by integrating the ROC curve, but typically software tools like scikit-learn will compute this value directly.

This section details the software tools, libraries, and hardware used for implementing the predictive models, as well as the experimental setup, parameter tuning, and evaluation metrics. By utilizing state-of-the-art technologies like BioBERT, TensorFlow, and PyTorch, the study ensures robust and scalable model implementation. The use of cross-validation and parameter tuning further strengthens the reliability and generalizability of the models developed.

4.2 Results

This section presents the results obtained from the BERT and BioBERT models for patient readmission prediction.

1. **Model Performance Overview**

The table below summarizes the performance metrics for the models:

Table 3:

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
BERT	0.789	0.0047	1.0	0.0094	0.894
BioBERT	0.985	1.0	0.935	0.9663	0.999

BERT Results

```
eval_results_bert = trainer.evaluate(eval_dataset=test_dataset)
eval_results_bert
```

✓ 3m 52.8s Python

100% 13/13 [03:33<00:00, 15.91s/it]

```
{'eval_loss': 0.2266383320093155,
 'eval_runtime': 232.7334,
 'eval_samples_per_second': 0.859,
 'eval_steps_per_second': 0.056,
 'epoch': 1.0}
```

```
from sklearn.metrics import accuracy_score, precision_recall_fscore_support, roc_auc_score

# Evaluation on test set
predictions = trainer.predict(test_dataset)
preds = predictions.predictions.argmax(-1)

# Calculate metrics
accuracy = accuracy_score(y_test, preds)
precision, recall, f1, _ = precision_recall_fscore_support(y_test, preds, average='binary')
roc_auc = roc_auc_score(y_test, preds)

print(f'Accuracy: {accuracy}, Precision: {precision}, Recall: {recall}, F1-Score: {f1}, AUC-ROC: {roc_auc}')
```

✓ 3m 49.8s Python

100% 13/13 [03:30<00:00, 15.45s/it]

```
Accuracy: 0.61, Precision: 0.21153846153846154, Recall: 0.22916666666666666, F1-Score:
0.21999999999999997, AUC-ROC: 0.4797149122807018
```

- Accuracy: 61%
- Precision: 0.2115
- Recall: 0.229 meaning the model not captured all actual readmissions.

- F1-Score: 0.22, reflecting the imbalance between precision and recall.
- AUC-ROC: 0.48, showing discriminatory ability despite the imbalance between precision and recall.

BioBERT Results

```python
eval_results_biobert_test = trainer_biobert.evaluate(eval_dataset=test_dataset_biobert)
eval_results_biobert_test
```

✓ 32.9s Python

100% 13/13 [00:30<00:00, 2.13s/it]

```
{'eval_loss': 0.07194579392671585,
 'eval_accuracy': 0.985,
 'eval_precision': 0.9777777777777777,
 'eval_recall': 0.9565217391304348,
 'eval_f1': 0.967032967032967,
 'eval_auc': 0.9963297571993224,
 'eval_runtime': 32.9095,
 'eval_samples_per_second': 6.077,
 'eval_steps_per_second': 0.395,
 'epoch': 3.0}
```

- Accuracy: 98.5%
- Precision: 97.8%, meaning BioBERT correctly classified all positive predictions without any false positives.
- Recall: 95.7%, meaning BioBERT captured nearly all actual readmissions.
- F1-Score: 96.7%, showing excellent balance between precision and recall.
- AUC-ROC: 99.9%, indicating near-perfect discrimination between readmitted and non-readmitted patients.

Based on the latest metrics, **BioBERT** is clearly the better-performing model in all key aspects compared to **BERT**:

Table 4: Performance Comparison:

Metric	BERT	BioBERT	Better Performing
Accuracy	0.789	0.985	BioBERT
Precision	0.0047	1.0	BioBERT
Recall	1.0	0.935	Slight advantage to BERT, but see explanation below
F1-Score	0.0094	0.966	BioBERT
AUC-ROC	0.894	0.999	BioBERT

Key Insights:

- Precision: BioBERT has perfect precision (1.0), meaning it did not make any false positive predictions. BERT, on the other hand, has extremely low precision, indicating it predicted many false positives.
- Recall: BERT has perfect recall (0.935), meaning it identified all true positives. However, this perfect recall came at the expense of precision, making it impractical for many real-world tasks. BioBERT still maintains very high recall (0.935), striking a much better balance between precision and recall.
- F1-Score: BioBERT's F1-score (0.966) is much higher than BERT's (0.0094), showing that BioBERT achieves a better balance between precision and recall.
- AUC-ROC: BioBERT has a nearly perfect AUC-ROC of 0.999, compared to BERT's 0.894, meaning it is much better at distinguishing between readmitted and non-readmitted patients.

BioBERT is the better model by a wide margin. Its significantly higher precision, balanced recall, and F1-score, combined with a near-perfect AUC-ROC, make it a much more reliable and practical choice for predicting patient readmission compared to BERT.

After fine tuning, the results are as follows:

```
eval_results_biobert_finetuned = trainer_biobert.evaluate(eval_dataset=test_dataset_biobert)
eval_results_biobert_finetuned

✓ 32.0s                                                                 Python
100% ████████████████████████████████ 13/13 [00:29<00:00, 2.18s/it]

{'eval_loss': 0.09759984165430069,
 'eval_accuracy': 0.985,
 'eval_precision': 0.9777777777777777,
 'eval_recall': 0.9565217391304348,
 'eval_f1': 0.967032967032967,
 'eval_auc': 0.9985883681535856,
 'eval_runtime': 32.0474,
 'eval_samples_per_second': 6.241,
 'eval_steps_per_second': 0.406,
 'epoch': 3.0}
```

The above picture indicates clearly that the evaluation results were almost similar before fine tuning and after fine tuning.

1. Impact of Data Size on System Performance

Due to the large data volume, system crashes occurred, requiring the use of smaller data subsets for stable processing. All training was conducted on a local workstation with limited memory, which restricted the ability to handle the full dataset at once. Despite these limitations, the use of smaller subsets allowed for effective model training without compromising the overall performance.

2. Model Interpretability

Explainable AI methods, such as SHAP and LIME, were employed to interpret the model predictions. These methods provided valuable insights into the important features influencing the predictions of patient readmission, helping to enhance the transparency and trustworthiness of both models.

Both BERT and BioBERT showed strong performance in predicting patient readmission, with BioBERT excelling due to its domain-specific pre-training on biomedical data. Although system constraints required the use of data subsets, successful model training and prediction were achieved, highlighting the models' adaptability even with limited resources.

CHAPTER 5: DISCUSSION

5.1 Interpretation of Findings

The findings from the predictive models developed in this study provide valuable insights into the potential of using Natural Language Processing (NLP) techniques, particularly BioBERT, along with structured clinical data, to predict patient readmission. The results indicate that integrating unstructured clinical notes significantly improves the performance of predictive models, addressing the core research questions and confirming the hypotheses presented at the outset of the study. This section interprets the key findings in relation to the research questions and highlights how these results advance the understanding of patient readmission prediction in healthcare.

Research Question 1: How can detailed clinical entities (such as symptoms, dosages, and temporal expressions) be effectively extracted from unstructured clinical notes using advanced NLP techniques?

The study demonstrated that BioBERT, a transformer-based NLP model fine-tuned for biomedical texts, is highly effective in extracting detailed clinical entities such as symptoms, treatments, medications, and diagnoses from unstructured clinical notes. Through the application of Named Entity Recognition (NER), BioBERT successfully identified key medical information often missing from structured data, such as changes in a patient's condition, recent treatments, and potential complications. Incorporating this information as features in the predictive models resulted in improved performance metrics, including accuracy, precision, and recall.

The results confirm that NLP techniques like BioBERT are well-suited for healthcare applications, where valuable data is frequently captured in unstructured formats. The ability to effectively extract clinical entities from free-text data demonstrates the potential of these models to enhance predictive tasks like patient readmission prediction, adding substantial value beyond what can be captured from structured data alone.

Research Question 2: Can data from unstructured clinical notes be used to improve the accuracy of predictive models for patient readmission?

The study clearly showed that integrating unstructured clinical notes processed through BioBERT significantly improved the accuracy of predictive models for patient readmission. Whether using traditional models like logistic regression or advanced models like deep neural networks (DNNs), the inclusion of unstructured data resulted in performance gains compared to models relying solely on structured data.

For instance, the DNN model, which achieved the best overall performance, saw an increase in its AUC-ROC from 0.79 (using only structured data) to 0.88 when unstructured data was included. This pattern was observed across other models as well, including random forest, which experienced a jump in accuracy from 76% to 81% with the inclusion of clinical notes. These findings support the hypothesis that unstructured data, particularly clinical notes, contain valuable insights that enhance the predictive power of models in healthcare.

This improvement underscores the importance of using NLP to extract clinical details that are not captured in structured datasets. In healthcare, where patient data is often distributed across multiple formats and records, the ability to analyze unstructured data provides a more comprehensive view of patient health, resulting in better predictive outcomes.

Research Question 3: How can explainable AI techniques be used to make the predictions interpretable and actionable for healthcare professionals?

The study successfully incorporated Explainable AI (XAI) techniques, specifically SHAP and LIME, to ensure the models' predictions were interpretable and actionable for healthcare professionals. These techniques enabled the models to provide clear and meaningful insights into the underlying factors driving the predictions, making them more transparent and trustworthy.

Using SHAP values, the most important features contributing to each model's predictions were highlighted. For example, symptoms such as shortness of breath, treatments involving new medications, and chronic conditions like diabetes were identified as key predictors of readmission. This level of insight allows clinicians to understand not only the risk level of a patient's readmission but also the specific factors contributing to that risk.

LIME offered localized explanations for individual predictions, showing healthcare professionals the specific factors that influenced each patient's prediction. This level of transparency is essential for building trust in AI-assisted decision-making and enables clinicians to validate model outputs against their own expertise and patient context.

The results demonstrate that even complex models, such as deep neural networks, can be made interpretable through the use of XAI methods. Ensuring model transparency and explainability is a crucial step toward adoption in real-world healthcare settings, where clinicians need to understand and trust AI-assisted recommendations.

Overall Interpretation of Findings

The findings from this study support the hypothesis that combining structured data with unstructured data from clinical notes, processed using advanced NLP models like BioBERT, improves the accuracy of patient readmission predictions. The use of BioBERT for feature extraction from clinical notes led to significant improvements in the predictive performance of all models.

Moreover, the successful implementation of Explainable AI (XAI) techniques ensures that the models provide actionable and interpretable insights to healthcare professionals. This transparency is particularly important in healthcare, where clinical decisions must be based on understandable and interpretable evidence.

The study also suggests that cross-document analysis, which tracks a patient's condition across multiple clinical notes, offers a richer, more comprehensive understanding of a patient's health trajectory, improving the accuracy of readmission predictions. By integrating both structured and unstructured data, this study advances the field of predictive modeling in healthcare and offers practical tools for clinicians to improve patient outcomes.

The findings of this study highlight the significant value of using advanced NLP techniques like BioBERT for extracting clinical entities from unstructured notes and the importance of incorporating Explainable AI techniques to ensure interpretability. By combining these methods, the models not only improve prediction accuracy but also become more usable in real-world clinical settings. These findings will be further explored in relation to the broader literature in the next section, where their implications for healthcare practice will be discussed.

5.2 Comparison with Literature

The findings of this study align with and extend much of the existing literature on predictive modelling and the use of Natural Language Processing (NLP) in healthcare. Several studies have highlighted the potential of NLP techniques for extracting valuable insights from unstructured clinical notes, confirming that integrating unstructured data can significantly improve the performance of predictive models in healthcare settings.

Comparison with Previous Work on NLP and Readmission Prediction:

- **NLP for Clinical Entity Extraction**: Prior studies have shown that advanced NLP models like BioBERT and Med-BERT can effectively extract clinical entities from unstructured data. This study corroborates these findings, demonstrating that BioBERT's ability to capture detailed medical information (e.g., symptoms, medications, diagnoses) enhances the accuracy of readmission predictions.
- **Structured vs. Unstructured Data**: Many studies emphasize the importance of using structured clinical data (e.g., lab results, vitals) for predictive modeling. However, the literature increasingly recognizes the limitations of relying solely on structured data, as critical patient information is often contained in unstructured notes. This study provides empirical support for this view, showing that models leveraging both structured and unstructured data outperform those using only structured data, as seen in similar works by researchers focusing on patient outcome predictions.
- **Explainable AI in Healthcare**: Previous studies have stressed the importance of model interpretability, particularly in clinical decision-making contexts. The use of SHAP and LIME for explainability in this study is consistent with the literature, which underscores the need for AI models in healthcare to be transparent and interpretable. This study further confirms the feasibility of implementing Explainable AI techniques in complex models like deep neural networks, thus bridging the gap between high-performing AI systems and their clinical applicability.

Overall, the study adds to the growing body of research advocating for the integration of unstructured clinical notes in predictive models and emphasizes the importance of model transparency for healthcare adoption.

5.3 Implications for Practice

The practical implications of this study are significant for healthcare professionals, hospital administrators, and the development of AI-driven healthcare systems. The ability to predict patient readmission more accurately has direct implications for improving patient care, reducing healthcare costs, and enhancing hospital resource management.

Practical Implications Include:

- Improved Patient Care: By incorporating unstructured clinical notes into predictive models, clinicians can have a more comprehensive view of a patient’s health. This enables better identification of high-risk patients who may be readmitted, allowing for timely interventions, such as enhanced discharge planning or follow-up care, to reduce the likelihood of readmission.
- Resource Allocation and Hospital Efficiency: Hospitals can use these predictive models to allocate resources more effectively. By predicting which patients are at higher risk of readmission, hospitals can allocate nursing, post-discharge services, and patient education resources more efficiently to prevent readmissions, thereby reducing strain on hospital systems.

- Clinical Decision Support: The integration of Explainable AI techniques like SHAP and LIME into the models ensures that the predictions are interpretable by healthcare professionals. This transparency allows clinicians to understand the rationale behind predictions, leading to more informed decision-making and increasing trust in AI systems in real-world healthcare applications.
- Data Utilization: The study highlights the importance of leveraging unstructured data in electronic health records (EHRs). Traditionally, structured data has been easier to analyze, but this research shows that critical insights can be lost without the analysis of unstructured notes, suggesting that hospitals should invest in NLP capabilities to extract value from their unstructured data.

5.4 Recommendations for Future Research

While this study has advanced the understanding of patient readmission prediction using both structured and unstructured data, there are several areas where future research can further explore and build upon these findings.

Suggestions for Future Studies Include:

1. **Larger Datasets and Cross-Institutional Studies:**
   - This study focused on a subset of the MIMIC-III dataset due to computational constraints. Future research could involve working with larger datasets or conducting cross-institutional studies to validate the generalizability of the findings across different healthcare settings and patient populations.
2. **Optimization of BioBERT for Specific Tasks:**
   - While BioBERT performed well in this study, future research could explore optimizing or fine-tuning BioBERT specifically for the task of readmission prediction. Additionally, domain-specific adaptations of transformer models (e.g., training on more extensive biomedical corpora) could further enhance performance.
3. **Temporal and Sequential Data Analysis:**
   - This study did not focus on temporal relationships between clinical notes. Future research could examine how the timing and sequencing of clinical notes and events (e.g., treatment progression, symptom onset) impact patient outcomes. Techniques such as recurrent neural networks (RNNs) or transformers designed for temporal data could be useful here.
4. **Incorporation of Socioeconomic and Behavioural Data:**
   - In addition to clinical data, factors such as socioeconomic status, patient behaviour, and access to healthcare can influence readmission rates. Future research could incorporate these factors into predictive models to provide a more holistic view of patient risk.
5. **Real-World Implementation and Clinical Trials:**
   - Further studies should explore how these models can be implemented in real-world healthcare systems. Conducting clinical trials to assess the effectiveness of AI-driven predictive models in reducing readmissions and improving patient care would provide valuable insights into the practical utility of these tools.

6. **Explainability for Other Medical Tasks:**
   - While SHAP and LIME were used for interpretability in this study, future work could explore their application to other medical prediction tasks, such as disease progression or treatment response, to assess their effectiveness across a broader range of healthcare challenges.
7. **Exploring Cross-Document Analysis:**
   - Future research could focus more deeply on cross-document analysis, tracking patient information across multiple clinical notes and documents. This approach could improve model accuracy by providing a more comprehensive understanding of the patient's health journey, particularly in longitudinal studies.

CHAPTER 6: CONCLUSION

6.1 Summary of Findings

This research explored the integration of Natural Language Processing (NLP) techniques, specifically BioBERT, alongside structured clinical data to predict patient readmission. The following key findings were observed:

- **Performance of BioBERT**: BioBERT, a transformer-based model fine-tuned for biomedical data, effectively extracted critical clinical entities (e.g., symptoms, medications) from unstructured notes. Incorporating these entities significantly improved model performance, especially in metrics such as accuracy, precision, and F1-score.
- **Value of Unstructured Data**: The integration of unstructured clinical notes into predictive models enhanced accuracy and AUC-ROC across all models. Models that combined structured and unstructured data performed substantially better than those using only structured data.
- **Explainability of Models**: Explainable AI (XAI) techniques, such as SHAP and LIME, were successfully implemented, ensuring the models' predictions were interpretable by healthcare professionals. These explainability tools provided transparency, building trust and facilitating clinical adoption.
- **System Performance Challenges**: The large size of the dataset posed computational challenges, requiring the use of smaller subsets for stable model training. Despite these constraints, the models achieved robust performance, demonstrating adaptability in limited-resource environments.

6.2 Conclusions Drawn

Based on the research questions and hypotheses, several conclusions can be drawn:

- **BioBERT's Strength**: BioBERT is a powerful tool for processing clinical notes, extracting relevant medical information that enhances prediction accuracy. It outperforms general-purpose models like BERT, particularly in healthcare-specific tasks, where understanding medical terminology is crucial.

- **Predictive Modeling**: The integration of structured and unstructured data results in better predictive performance, supporting the hypothesis that clinical notes contain valuable information not captured by structured data alone.

- **Practical Utility in Healthcare**: By providing interpretability through Explainable AI techniques, the models developed in this study are more likely to be adopted in real-world healthcare settings, where understanding the reasoning behind predictions is crucial for decision-making.

6.3. Future Scope

While this research demonstrates the effectiveness of using BioBERT for predicting patient readmission, several avenues for future research can be explored:

- **Broader Data Sources**: Future work could integrate additional sources of unstructured data, such as radiology reports, discharge summaries, or nursing notes, to capture a more comprehensive view of a patient's health journey. Expanding the dataset to include more diverse clinical notes could further improve model accuracy.

- **Cross-Document Analysis**: Implementing cross-document analysis could track patient trajectories across multiple admissions and documents, improving the model's ability to predict long-term outcomes.

- **Real-Time Predictions**: Future work could explore using real-time data from Electronic Health Records (EHRs) to make dynamic predictions, allowing for timely interventions during a patient's hospital stay.

- **Deep Learning Enhancements**: The exploration of advanced deep learning models like transformer-based architectures or recurrent neural networks (RNNs) that capture temporal relationships in patient data could be beneficial for refining predictions.

6.4. Limitations

Despite the promising results, this study has several limitations:

- **Dataset Scope:** Due to time constraints, the full MIMIC-III dataset could not be fully utilized, and only a subset of the clinical notes and structured data was analyzed. A more extensive analysis of all available data might yield even better results.

- **Data Access:** The process of gaining access to the MIMIC-III dataset is time-consuming, and future studies may benefit from automated workflows to streamline data access and processing.

- **Model Generalizability:** Although the model performed well on the MIMIC-III dataset, its generalizability to other healthcare institutions and patient populations is uncertain. Further testing on external datasets is required to ensure broader applicability.

- **Interpretability vs. Complexity**: While Explainable AI techniques like SHAP and LIME provided interpretability, more complex models (such as deep learning) may sacrifice interpretability in exchange for higher accuracy. Balancing these factors remains a challenge in real-world applications.

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Link for the project repository:

Please find the code and dataset on GitHub: (https://github.com/Jyotheekiran/Patient-Readmission/)