CHAPTER I
INTRODUCTION

1.1 Background

Cancer is one of the most feared diseases of the twentieth century and a significant public health problem. Cancer is a serious and potentially life-threatening disease that can have a devastating impact on individuals and their families [1]. Cancer diagnosis and treatment are life-changing experiences that demoralize cancer patients. The journey through diagnosis, treatment, and the aftermath of living with or surviving cancer often leads to a range of mental health challenges [2]. The emotional effects, such as depression, anxiety, and stress, significantly diminish the well-being and quality of life of those affected. This challenge is compounded by the diverse and complex nature of cancer treatments, including chemotherapy and radiation, which can further destabilize a patients mental health. Over the past decade, there has been a rapid accumulation of evidence regarding the influence of mental health on tumor progression and cancer-related mortality. Another study found that approximately half of cancer patients report experiencing clinical levels of distress [2].

Globally, about 450 million people worldwide are mentally ill, accounting for 13% of the global disease burden [3]. Assessing mental health among cancer patients is crucial for identifying individuals who may require additional support, thorough evaluations, and follow-up interventions. However, traditional detection methods often fall short in terms of accuracy and efficiency, particularly when navigating the complex emotional landscapes that characterize medical contexts. These conventional approaches struggle to interpret the nuanced meanings embedded in textual information, often conveying a rich tapestry of human emotion and insights. Traditionally, mental health detection relies on face-to-face interviews, self-reports, or questionnaire distribution, which are typically labor-intensive and time-consuming [3]. Several studies have explored the use of technology to improve mental health detection. This research proposes an innovative strategy that leverages the wealth of textual data to detect mental health, particularly depression, in cancer patients on social media platforms.

Social media platforms like Twitter, Facebook, and Instagram are increasingly used by many people to share their thoughts and views [4]. They can share, co-create, or exchange various forms of digital content, including information, messages, photos, or videos. The emotion and language found in social media posts can reflect feelings of worthlessness, guilt, helplessness, and self-hatred, which are characteristic of major depression [4]. Exploratory studies indicate that individuals facing mental health challenges often turn to social media as a

means of sharing their personal experiences, seeking information about their conditions and treatment options, and providing or receiving support from others navigating similar difficulties [5].

Table 1.1 Literature Review

No	Judul	Author	Published in	Model	Dataset	Hasil
1	Recognizing Depression from Twitter	Sho Tsugawa, Yusuke Kikuchi, Fumio Kishino, Kosuke Nakajima, Yuichi Itoh, Hiroyuki Ohsaki	CHI 2015	SVM	Twitter, Questionnare CESD (Center of Epidemiologic Studies Depression Scale)	SVM : 69%
2	An hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM	Harnain Kour, Manoj K.Gupta	Springer 2022	RNN, CNN, CNN-Bi-LSTM		RNN : 90.66% CNN : 91.73% CNN-Bi-LSTM : 94.28%
3	Depression Detection on Twitter Using RNN and LSTM Models	Abhyudaya Apoorva, Vinat Goyal, Aveekal Kumar, Rishu Singh, and Sanjeev Sharma	Springer 2023	RNN, LSTM	Twitter API, sentiment140	RNN : 95.98% LSTM: 96.21%
4	A Novel Text Mining Approach for Mental Health Prediction Using Bi-LSTM and BERT Model	Kamil Zeberga, Muhammad Attique, Babar Shah, Farman Ali, Yalew Zelalem Jember, and Tae-Sun Chung	Computational Intelligence and Neuroscience	Bi-LSTM dan BERT Model	Twitter dan Reddit API	LSTM:94% BILSTM : 96%
5	An Attention-based CNN-BiLSTM model for depression detection on social media text	Joel Philip Thekkekara, Sira Yongchareon, Veronica Liesaputra	Elsevier 2024	LSTM, Bi-LSTM, CNN	CLEF2017	LSTM: 94.26% BILSTM:94.3% CNN:95.41%
6	Hybrid Machine Learning Models to Detect Signs of Depressions	Shakir Khan, Salihah Alqahtani	Springer, 2024	ANN, SVM	Twitter	ANN:99% SVM : 92%
7	Diagnosis of Depression Based on Four-Stream Model of Bi-LSTM and CNN from Audio and Text Information	A-Hyeon Jo, Keun Chang Kwak	IEEE Access 2022	BiLSTM dan CNN	EDAIC - WOZ (Extended Distress Analysis Interview Corpus Wizard of Oz)	Bi-LSTM:71% CNN : 65%
8	A hybrid model	Vandana, Nikhil	Elsevier 2023	LSTM, BI-	DAIC - WOZ	CNN:92%

	for depression detection using deep learning	Marriwala, Deepti Chaudary		LSTM, CNN		Bi-LSTM:88% LSTM : 80%
9	Deep Learning for Depression Detection from Textual Data		MDPI, 2022	RNN, LSTM	Twitter	SVM: 97.31% CNN: 91% LSTM : 89%
10	Ensemble Hy brid Learning Methods for Automated Depression Detection	Luna Ansari, Shaozing Ji, Qien Chen, Erik Cambria	IEEE Xplore, 2023	LSTM	Reddit	75%

In 2011, a researcher from Japan assessed the effectiveness of analyzing users social media activities, specifically on Twitter, to estimate levels of depression. The study found that it possible to identify signs of depression in users with an accuracy of about 69% with an SVM model [6]. Another research study, focused on detecting mental health conditions through social media, employed the Long Short-Term Memory (LSTM) algorithm to identify users exhibiting depression based on their tweets. This approach achieved a validation accuracy of 96.21% and a validation loss of 0.1077. These results highlight the effectiveness of the LSTM model in recognizing mental health issues [7].

Based on review previous research, in Table 1.1 number 3,5,7,8,10 primarily focused on depression detection using various machine learning and deep learning such as LSTM, Bi-LSTM, CNN, and RNN. However, this study expands the scope by detecting not only depression but also anxiety and stress, thereby providing a more comprehensive mental health analysis. Moreover, while previous research utilized data from the public tweet. This research specifically targets cancer patients, who tend to have different risk factors and mental health disorders patterns compared to the public. In terms of the model, this research implements LSTM with attention layer. LSTM is a type of Recurrent Neural Network, this model specifically designed to remember long-term dependencies in sequential data [8]. LSTM has three gates to extract hidden features, including a forget gate, an input gate, and output gate [9]. LSTM with attention helps the model focus more on keywords related to mental health indicators. This attention mechanism not only improves prediction accuracy but also makes the model more interpretable by highlighting the most influential text segments. This study not only broadens the scope of mental health detection but also enhances performance through a more targeted and specific approach.

1.2 Problem Identification

The motivation for conducting this research stems from the limitations of conventional detection methods in identifying mental health conditions in cancer patients. Traditional approaches often lack accuracy, efficiency, and the ability to understand the complexities of mental health symptoms. This highlights the need for advanced technology, utilizing deep learning, to enable early detection of mental health indicators, providing more precise and effective results.

1.3 Objective and Contributions

The objective of this research is to make meaningful contributions to deep learning and mental health care, particularly through social media platforms like Twitter. The primary focus is to create a new system for early detection and ongoing support for cancer patients. To achieve this goal, the study will develop an LSTM with attention mechanism. This model is specifically designed to analyze textual data from tweets in the English language. This approach is expected to enhance the detection of mental health issues among cancer patients.

1.4 Scope of Work

This thesis focuses on developing an advanced framework identifying mental health indicators, particularly depression, among cancer patients. The approach involves a meticulous process of extracting features from data, implementing knowledge transfer techniques, and harnessing the unique strengths of LSTM networks for in-depth textual analysis by collecting data from Twitter, such as through the Twitter API or Kaggle. The framework seeks to provide a more comprehensive understanding of the emotional and mental health challenges faced by cancer patients.

1.5 Research Methodology

This section discusses the methodology that has been considered in this research in sequence order to meet the objectives of this study. The detailed workflow of our proposed framework is organized into three subsections:

1. Study Literature: This involves researching and reviewing previous studies and scientific literature related to mental health detection, social media analysis, and deep learning techniques.
2. Design System model: The system model outlines the overall structure and components

needed to achieve the goal of automated mental health detection.

3. Dataset: This is the collection of data needed to train and test the model. For this project, the dataset would consist of social media posts from platforms like Twitter.
4. Text Preprocessing: This step involves cleaning and preparing the text data for analysis. Since social media posts often contain informal language, hashtags, emojis, special characters, and URLs.
5. Feature Extraction: Extract patterns related to specific words frequently used by individuals experiencing depression, based on findings from conventional studies.
6. Random Over Sampling: Random Over Sampling is a technique used to address class imbalance in datasets, especially in classification tasks. In many real-world scenarios, certain classes may be underrepresented, which can cause a model to become biased toward the majority class.Word Embedding with Word2vec: Word2vec is a word embedding technique used to convert words into fixed-length numeric vectors that capture semantic meaning and contextual relationships between words.
7. Deep Learning Implementation: In this step, a deep learning model, such as an LSTM (Long Short-Term Memory) or another neural network architecture, is implemented. LSTM is designed to analyze text and sequential data, excelling in understanding long-term patterns through its internal mechanism. This involves integrating external memory architectures to enhance the model's ability to store and retrieve long-term dependencies from sequential data.
8. Result and Analysis: After training the model, the results are analyzed to evaluate the system's accuracy, precision, recall, F1 score, and other performance metrics. A comparative analysis is also conducted to assess the impact of memory augmentation on model performance.

1.6 Research Plan and Action Point

Table 1.2 this expanded timeline offers a more comprehensive breakdown of the key activities, milestones, and objectives associated with each stage of the thesis project.

Table 1.2 Research Timeline

Timeline / Activity	October	November	December	January	February
- Conduct Literature Review and Proposal - Define Requirements for system design - Collect social media data					
- Design system architecture for LSTM framework - Develop Initial components (data preprocessing, feature extraction, perform memory augmentation)					
- Build the LSTM framework and implement core components					
- Optimize LSTM Model - Train the model using collected cancer patients dataset					
- Validate model performance - Evaluate the framework on test data and compare it with LSTM model					
- Finalize the model and accuracy					