UK Wide Mental Health Crisis Prediction: Leveraging Time-Series Forecasting and Social Media Analysis

by

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DECLARATION

I hereby declare that the work presented in this project is my own, except where otherwise acknowledged.

Responsible Use of Generative AI

I affirm that generative AI tools were used in a transparent and responsible manner throughout the development of this project. Specifically, the following tools were utilized:

Code Generation: ChatGPT 4.0 was used to assist with the initial development of code snippets.

Code Debugging and Optimization: ChatGPT 4.0 was used to support the identification of code errors and for optimization.

Report Production: Gemini 2.5 Pro was used to assist with the structuring of the report and to refine the text for clarity, grammar, and formatting.

All outputs from these tools were subject to my critical review, validation, and editing to ensure accuracy, originality, and alignment with the project's objectives. The intellectual direction, core methodology, and final contributions of this project remain my own.

A detailed record of my interaction with these tools, including specific prompts and a critical reflection on their use, is included in the Appendix of this report.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my supervisor, Dr. Mubashir Ali, for his patient guidance, constructive feedback, and constant encouragement throughout this project. His insights into data science methodology and careful attention to detail shaped every stage of this dissertation. I am grateful to the academic and support staff of the School of Computer Science, University of Birmingham, for providing an engaging learning environment and timely assistance across the MSc in Data Science programme. My heartfelt thanks go to my friends and MSc cohort for their camaraderie, late-night debugging sessions, and thoughtful discussions that improved this work. Above all, I am deeply indebted to my family for their unwavering support, patience, and belief in me. Any errors that remain are entirely my own.

ABSTRACT

This research presents a comprehensive predictive model for forecasting nationwide mental health crises in the UK. The methodology employs a dual-stream approach, integrating time-series forecasting with real-time social media sentiment analysis. We leverage a suite of time-series models, including ARIMA, Prophet, and Long Short-Term Memory (LSTM) networks, to analyze historical trends in mental health data. In parallel, natural language processing (NLP) techniques are applied to social media data to perform sentiment analysis, thereby capturing shifts in public discourse and emotional states related to mental well-being. By synthesizing these structured and unstructured data sources, our system is engineered to predict future trends in mental health crises across the UK. The resulting predictive model is designed to provide early indications of potential increases in mental health issues, offering a valuable tool for policymakers and healthcare professionals to implement proactive and timely interventions.

Keywords: Mental Health Crisis, Time-Series Forecasting, Social Media Analysis, ARIMA, Prophet, LSTM, Natural Language Processing, Sentiment Analysis, UK.

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Chapter One

Introduction

Suicidality and mental health crisis generally, is a penetrating public health issue in the United Kingdom with far-reaching social and economic impacts **[House of Commons Library, 2025]**. Prevention of such crises at the appropriate time is essential for efficient provision of resources, preventive policy decision-making, and targeted intervention.

Prediction in this field has so far primarily relied on historical health information. Although useful, this methodology is inherently restricted. The dynamic, real-time changes in public mental health that can emerge in the run-up to a major crisis tend to be ignored by historic data, a lagging indicator because it gives an indication of what has just happened **[Public Health England, 2017**. One of the flaws in current prediction models is that early-warning signs that are subtle tend to often missed because of this emphasis on ordered, historical data.

This study bridges this gap by interlinking real-time social media discourse and traditional structured suicide information. We propose and contrast a new dual-stream forecasting model that combines natural language processing (NLP) of social media sentiment analysis and time-series forecasting of past suicide rates. The primary goal of this study is to construct and validate a predictive model that is utilizing both structured data and unstructured data to predict mental health crises in the UK more timely and accurately. A more robust and stable tool for both policymakers and clinicians, the model created by combining these two streams of data offers an anticipatory method of identifying increasing mental health hazards and helps to develop a more resilient public health response.

1.1 Motivation

In the United Kingdom, mental health crises, specifically suicide, are a major public health concern **[House of Commons Library, 2025]**. Whereas historical forecasting has relied on historic data, this method is usually not able to capture the pre-crisis, real-time signals contained in public language **[Public Health England, 2017]**. Social media, on the other hand, provides a vast, unstructured repository of user-produced content that poses an unconventional window on public sentiment and emerging trends in mental health.

Because studies have demonstrated that language on social media can indicate depression and psychological distress prior to diagnosis, this online discussion provides insightful, future-oriented information. Social media has already been demonstrated to improve prediction models, but currently, there is no integrated framework combining official statistics and real-time social media sentiment that is available for the UK as a whole **[De Choudhury, Counts, and Horvitz, 2013][Eichstaedt et al., 2018]**.

To enhance predictive mental health crises throughout the UK, this report conceptualizes and validates a dual-stream predictive model. By demonstrating the potential for a model that combines these two data streams to enhance the accuracy of mental health crisis predictions and lead to earlier and more effective public health interventions, the project aims to bridge a research gap.

1.2 Research Questions

This project aims to address the following main research questions, which collectively drive its analytic approach:

[1] How have UK suicide rates trended from 2005-2023, what are the demographic and regional patterns, and how do time-series models forecast these trends?

[2] How does social media sentiment surrounding mental health in the UK fluctuate from 2021-2025, and can these trends be forecasted to provide insight into the evolving online discourse?

[3] Does social media sentiment correlate with historical suicide rates, and can a combined model improve the reliability of mental health crisis forecasts?

1.3 Methodology

The approach employs a two-stream predictive model that combines unstructured social media data with structured official suicide statistics. Collection of data from two streams is the initial step in the process.

First, UK official suicide statistics from 2005–2023 will be extracted from the Northern Ireland Statistics and Research Agency (NISRA), the Office for National Statistics (ONS), and the National Records of Scotland (NRS). Second, raw, unstructured text data will be collected from the Reddit API on posts of UK subreddits from 2021 to 2025 concerning mental health. Each of the streams of data will have a particular modeling strategy employed. Time-series models like ARIMA, Prophet, and LSTM will be employed for projecting future trends in the historical suicide data **[Hyndman and Athanasopoulos, 2018]**. Natural Language Processing (NLP) methods will be used on the social media data. Latent Dirichlet Allocation (LDA) will be employed as topic modeling for extracting emerging themes and public sentiment **[Blei, Ng, and Jordan, 2003]**, whereas RoBERTa will be employed for sentiment analysis **[Liu et al., 2019]**. A full dataset to be utilized for the prediction of mental health crisis indicators will be constructed through combining structured suicide data and processed social media data. The last step is a rigorous testing of the model's performance. To further illustrate the advantages of social media insight integration, this will involve comparing past suicide rates with social media sentiment and conducting comparative analysis with a model that solely utilizes suicide data.

Chapter Two

Background

2.1 Background Information

Predictive modeling in the field of mental health as well as health is applying statistical and machine learning to predict future occurrences. For its success, this project employs quite a number of important models and concepts:

- **Models for Time Series Forecasting:**
- **ARIMA** (Autoregressive Integrated Moving Average): For forecasting stationary data in the short term, a standard statistical model works fine. It models previous residual errors and the relationship of an observation to its previous lagged observations. It might become weak with non-linear complexities and also require manual tuning.
- **Prophet:** Prophet is the forecasting framework built by Facebook. Prophet eases the process by automatically taking care of seasonality and missing data. Prophet works best with time series that contain seasonal patterns and for business use.
- **Long Short-Term Memory (LSTM):** This is a deep learning model and one of the type of recurrent neural network (RNN) which is best for identifying non-linear patterns and long-term correlations in time-series data. Although more computationally intensive than standard models, LSTMs are likely to provide better predictive results on complex datasets.

2.2 Related Work

Through analyzing key works that demonstrate some of the key features of predictive modeling for public health, the project's literature review systematically lays the groundwork for its new methodology. This discussion identifies the gap in the literature that the current project aims to fill.

- **Depression-related chatter on Twitter (De Choudhury et al., 2013:** In an effort to justify the use of social media data for mental health research, this key piece is crucial. In demonstrating that tweets may reveal symptoms consistent with a diagnosis of Major Depressive Disorder (MDD), it demonstrated Twitter's use as a window into depression in groups. The tweets in the study that were retrospectively analyzed contained reduced social interaction, elevated negative affect, and greater self-attentional focus in individuals with MDD, providing early evidence that social media data could be a useful method for measuring mental health trends **[De Choudhury, Counts, and Horvitz, 2013]**.

- **Social Media, Big Data, and Mental Health (Coppersmith et al., 2014):** The study also supports the use of social media methods to monitor mental health. The ability of "social media 'big data' in tandem with allied technologies like machine learning and natural language processing to inform key issues in population-level mental health surveillance and research" was investigated. The authors mention that social network sites like Twitter offer us opportunities to have access to "naturalistic, first person accounts of user behavior, thoughts, and feelings that may be indicative of emotional wellbeing," which gives the social media stream for this project a solid theoretical and methodological base. **[Coppersmith, Dredze, and Harman, 2014]**.

- **Non-deep learning models for time series classification in biomedical applications (Paparistodemou et al., 2022):** This systematic review supports the time-series forecasting component of this project's dual-stream approach. It shows that machine learning classifiers combined with engineered features extracted from time series data are a widely used and effective approach to biomedical applications. This result supports the project's methodology of utilizing organized time-series data for past suicides and combining it with other factors to build a more complete model. The use of advanced models, such as LSTM, in this project is also supported by the paper's emphasis on the new application of deep models to the high-dimensional and temporal nature of medical data **[Paparistodemou, Kosmas, and Preece, 2022]**.

- **Predicting Future Mental Illness from Social Media: A Big-Data Approach (Thorstad & Wolff, 2019):** Natural Language Processing research for predicting mental illness is very applicable in this paper. It built on existing research that had only worked with a single illness by developing a multi-classification method to predict multiple mental illnesses from the conversational language of social media. The main finding was that "everyday language contains cues to future mental illness, possibly before people are aware of their mental health status." However, the problem of "data bias and low model generalizability with homogeneous samples" is a significant shortcoming mentioned in other reviews **[1Thorstad and Wolff, 2019]**.

- **Systematic Review of Psychosis Prediction Models (Hunt et al., 2024):** Systematic review of psychosis prediction models. To establish deficit areas and identify current best practices, this systematic review integrated available evidence on psychosis prediction models. The results highlighted a notable "research-to-practice gap," which included the finding that "no model has been implemented in clinical practice" to date and that the majority of models had methodological flaws. The review once again emphasizes the need for more methodologically sound models, specifically designed for use in practice, particularly in the UK, as the most commonly employed clinical evaluation is based on the "At-risk mental state"(ARMS) criteria **[Hunt et al., 2024]**.

Synthesis of the Literature: These papers form the basis of this project. It combines the real-time, forward-looking insights provided by social media metrics, as indicated by the research of De Choudhury et al. and Coppersmith et al., with the rigorous, large-scale data analysis of a model such as the Nuffield Trust's (covered in Background Information), best placed to comprehend historical trends. The modern research considered by Paparistodemou et al., which highlights the need for models capable of handling the complexity of biomedical data, supports the use of sophisticated models in the project, specifically LSTM. The project attempts to address the problem of generalizability pointed out by Thorstad & Wolff by adapting the model to the UK's unique geographic and cultural setting. In addition, this study tries to directly address Hunt et al.'s systematic review's "research-to-practice gap" by looking at a model that is both methodologically sound and specifically tailored for policymakers.

Chapter Three

Data Collection

The project relies on a dual-stream approach to data collection, utilizing both traditional and non-traditional sources to create a comprehensive dataset for analysis.

3.1 Datasets

The datasets used in this research are summarized in the following table:

Data Stream	Source	Files Used	Time Period	Key Attributes
Historical Suicide Data	Official UK Government Data from the Office for National Statistics (ONS), National Records of Scotland (NRS), Northern Ireland Statistics and Research Agency (NISRA)	main (1).xlsx (ONS), probable-suicides-2023-data.xlsx (NRS), VS1130 Suicide and accidental deaths 2005 to 2023 - for web.xlsx (NISRA), MYE23_AGE_BANDS_NI_LGD.xlsx (NISRA)	2005-2023	Nation, Year, Sex, Age Group, Deaths, Rate (per 100,000)
Social Media Insights	Reddit API	N/A	2021-2025	Post Text, Timestamp, Sentiment, Topic

Table 3.1: Data Sources and Key Attributes

3.2 Dataset Description

To provide a comprehensive and precise review of historical suicide data across the UK, this study adopts a multi-source approach. Information was obtained from the "main (1)" for England and Wales and referenced the information from Tables 6 and 7, containing suicide numbers for the two countries, in an XLSX document that was made available by the Office for National Statistics (ONS) **[Office for National Statistics (ONS), 2024]**.

The "probable-suicides-2023-data.xlsx" spreadsheet was used to obtain suicide data for Scotland from the National Records of Scotland (NRS). Table_2A and Table_2B showed the number of deaths and suicide rate per 100,000 population, respectively **[National Records of Scotland (NRS), 2024]**.

Because of the nature of the data available, an integrated strategy was used for Northern Ireland. The suicide death numbers were taken from the "VS1130 Suicide and accidental deaths 2005 to 2023 - for web.xlsx" report, presented by the Northern Ireland Statistics and Research Agency (NISRA) **Northern Ireland Statistics and Research Agency (NISRA), 2024 Northern Ireland Statistics and Research Agency (NISRA), 2025**. To obtain the suicide rate per 100,000 population, the former was merged with mid-year population data in the "MYE23_AGE_BANDS_NI_LGD.xlsx" spreadsheet using data in the "Tabular (Age_5)" sheet **[Northern Ireland Statistics and Research Agency (NISRA), 2024]**. The different datasets were then combined into a single combined dataset, UK_Suicide_cleaned.csv, with Nation, Year, Sex, Age Group, Deaths, and Rate (per 100,000) columns from the period 2005 to 2023.

The social media data were retrieved from 2021 to 2025 through the Reddit API using a researcher-created bespoke Python script.Text posts about mental health across other UK subreddits form this unstructured dataset. Strict ethical principles were followed throughout the entire data collection period, and usernames and other identifiable metadata were removed in order to protect user anonymity and privacy. This stream provides live, unstructured public opinion and conversation, which are critical to the dual-stream predictive model.

Chapter Four

Implementation

Implementation process is designed to transform raw data into significant knowledge and a trustworthy predictive model. The process initiates with heavy data cleansing and preparation, followed by exploratory data analysis (EDA) for identifying trends and correlations among the datasets. A two-stream modeling approach is used subsequently—combining time-series forecasting of suicide data with social media content sentiment analysis. These streams are merged, and feature engineering is applied to generate a dataset for the final predictive model, which is tested for accuracy and performance.

4.1 Data Cleaning and Preprocessing

To guarantee the accuracy, consistency, and completeness of the historical suicide dataset as well as the social media data, a multi-step and essential data cleaning and preprocessing procedure was required.

4.1.1 Historical Suicide Data Cleaning and Preprocessing

The strategy was applied on data from each of the UK countries in order to enable future consolidation. The basic steps were:

- **Initial Reshaping (Wide-to-Long Format):** The initial wide shape of the raw data of all three nations was transformed into a long shape by transforming age groups into a single column. This was a simple reshaping of data undertaken using df.melt() to enable consistent time-series analysis for different demographic segments.
- **Column Renaming and Data Filtering:** Columns that had inconsistent or uninterpretable names were renamed to enhance readability (e.g., 'Area of usual residence \[note 2]' was renamed to 'Nation'). The datasets were filtered to emphasize between the years 2005 and 2023, and aggregate categories like Persons were removed to focus on sex-specific trends. The age group 10-14 was also removed because there wasn't enough data.
- **Data Type Conversion and Missing Value Handling:** Significant columns like 'Rate (per 100,000)' were particularly converted into numeric type via pd.to_numeric(). Deaths and Year columns were

converted into integer types. All rows with NaN values in key columns were dropped in order to ensure the dataset was complete.

- **Standardization:** Values in the Sex column were standardized from plural (Males, Females) to singular (Male, Female) to have consistency for the final combined dataset. Northern Ireland local district rows were filtered to retain only the national total.

4.1.2 Social Media Data Cleaning and Preprocessing

Unstructured social media data was handled with a distinct cleaning procedure to prepare it for analysis.

- **Combine Text Fields:** The selftext column and the title column were merged into a post_text column in order to fetch all relevant text. Missing values were handled with fillna("").
- **Convert to Datetime:** The created_utc column containing a Unix timestamp was converted to a human-readable datetime format, which would be essential for subsequent time-series analysis.
- **Remove Duplicates and Nulls:** The data was cleaned by stripping duplicate rows on the post_text content and any rows where post_text was null, to provide a clean dataset of unique posts.
- **Text Preprocessing:** A bespoke preprocess() function was applied to clean the text data. This function executed a set of transformations that included converting text to lower case, stripping URLs and newline characters, tokenization, lemmatization, and stopword removal.

4.1.3 Combined Dataset Preprocessing

The final step in data cleaning was to prepare the cleaned, individual-nation suicide data for merging with the social media data.

- **Load and Initial Type Conversion:** The UK_Suicide_cleaned.csv dataset was imported, and the Year column was typed as numeric explicitly. The errors="coerce" argument was also used to automatically convert any non-numeric values to NaN, a form of data cleaning.
- **Handling Missing Values and Final Type Casting:** The rows with NaN values in the Year column were dropped. The Year column was also cast to type integer for consistency and to convert it into discrete numerical value for plotting and grouping.
- **Data Filtering:** The suicide data was filtered to only include the years 2021 to 2023. This was a critical preprocessing task to align the two datasets temporally to a valid comparison.

4.2 Feature Engineering

The feature engineering involved creating new meaningful variables or modifying the existing ones to derive better representations of the underlying data and further support follow-up analysis.

4.2.1 Historical Suicide Data Feature Engineering

This was a necessary step in pre-processing the time-series data to utilize for effective trend analysis and prediction.

- **Age Group Consolidation:** The initial age groups (e.g., 15-19, 20-24) were converted into broader, more convenient categories (e.g., 15-34). This data consolidation reduced the granularity to reveal more general patterns and facilitate comparable comparisons.
- **Rate Calculation and Population Aggregation:** For Northern Ireland, a new feature, Rate (per 100,000), was specifically calculated using the deaths and population data and the formula (Deaths/Population) 100,000. The raw population data was also aggregated first by Year, Sex, and the newly formed broad Age Group to create a new feature in the form of total population for each demographic subgroup for each year.
- **Data Aggregation (Summary):** The cleaned data was combined by Year, Nation, Age Group, and Sex, adding up all of the deaths and calculating the average rates. Each row in the new, summarized dataset produced by this process represented a new feature for a particular demographic group in a given year.
- **Adding a "Nation" Column:** The Scotland and Northern Ireland datasets each included a "Nation" column added to them. This was an essential engineered feature that made the final concatenation of data from every UK nation into a single, merged dataset possible.

4.2.2 Social Media Data Feature Engineering

Advanced feature engineering techniques were applied to the social media text data to extract quantifiable features with meaning for analysis.

- **Sentiment Analysis (Chunked):** Sentiment was trained as an engineered feature using a pre-trained RoBERTa model. Since the model has a token limit, text was chunked and the sentiment label (Positive, Negative, or Neutral) was labeled as the most frequent sentiment of the chunks. The sentiment_label column was made a leading engineered feature.
- **Topic Modeling (LDA):** The advanced technique extracted underlying topics from the unstructured text. A CountVectorizer was used to create a Document-Term Matrix (DTM), and a LatentDirichletAllocation (LDA) model was trained to find underlying topics. For each post, the most probable topic was assigned, creating a new categorical topic feature.
- **Crisis Classification:** An important binary target feature, crisis, was created to filter posts that indicate a potential mental health crisis. By applying a list of pre-defined crisis_keywords, a new feature was generated to indicate the ground truth for building a classification model.

4.2.3 Combined Dataset Feature Engineering

These steps created new and more informative features or converted the data to allow the final combined analysis and modeling.

- **Aggregation and Summarization:** This was the first step in feature engineering for the time-series correlation.
- **Suicide Data:** The filtered suicide data was summarized by Year. For each year, a new feature was built by aggregating the Deaths (Suicide_Deaths) and another by calculating the mean of the Rate (per 100,000) (Suicide_Rate(per 100,000)). This aggregated the detailed demographic data to a condensed, year-level summary.
- **Reddit Data:** Similarly, the Reddit data was aggregated by Year. New columns were added: num_posts (a sum of posts) and avg_sentiment (an average of a sentiment polarity score).
- **Merging Datasets:** The merged Reddit and suicide dataframes were joined based on a common key (Year) to create a new, unified DataFrame. The new DataFrame contained characteristics from both of the original datasets, enabling cross-dataset analysis and being the merged dataset for the dual-stream model.
- **Column Renaming for Visualization:**The columns of the final merged DataFrame were renamed to be more descriptive and visually appealing, particularly for the correlation heatmap. For instance, Suicide_Rate(per 100,000) was changed to a more presentable 'Suicide Rate (per 100,000)'. This is one form of feature engineering for visualization.

4.3 Exploratory Data Analysis(EDA)

Before performing the predictive modeling task, exploratory data analysis (EDA) was conducted in an attempt to have a clearer view of the ready datasets, look for patterns, and validate crucial relationships. Three components made up the analysis: aggregated analysis of the two datasets, past suicide records time-series analysis, and social media sentiment analysis.

4.3.1 Time-Series Analysis of Historical Suicide Data

The initial EDA was conducted using the historical suicide data from 2005 until 2023.

- **Total Deaths and Rates by Nation:** The bar graph (Figure 4.1) indicates the striking difference in the rate of suicide deaths within the UK, with the highest in England, followed by Scotland, Wales, and Northern Ireland. The size of the population is largely to be held responsible. Another picture is presented by a second bar chart (Figure 4.2) of the mean rate per country. Scotland and Northern Ireland frequently report above the mean rates per 100,000 population of England and Wales, indicating there are important regional variations that are more than a question of simple population numbers

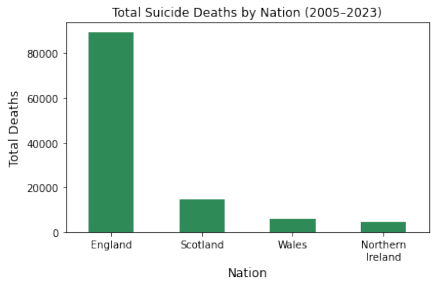

Figure 4.1: Total Suicide Deaths by Nation in UK

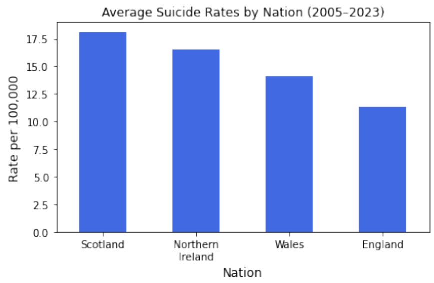

Figure 4.2: Suicide Rates by Nation in the UK

- **Suicide Trends Over Time (UK-wide):** A line graph of total suicide deaths for all the UK between 2005-2023 (Figure 4.3) shows a wavelike yet generally increasing pattern, with an extremely high peak in later years of the 2010s. This overall trend line provides an essential baseline for the ensuing time-series forecast. A line graph of the average year-on-year suicide rate (Figure 4.4) shows a more erratic trend with extreme highs and lows. The two-visualisation approach provides a more complete picture of suicide trends in the UK.

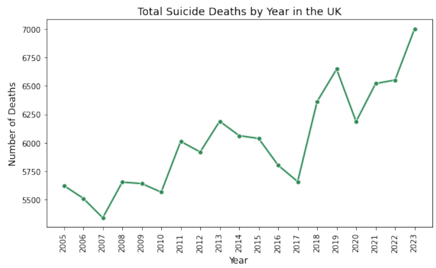

Figure 4.3: Historical Suicide Deaths in UK (2005-2023)

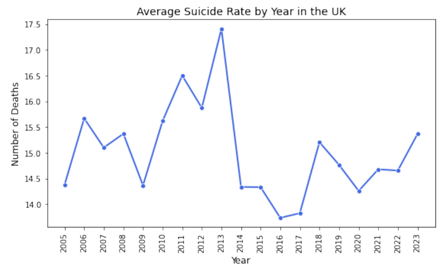

Figure 4.4: Historical Suicide Rates in UK (2005-2023)

- **Demographic Breakdown (UK-wide):** The UK-wide breakdown of suicide statistics displays some important demographic trends. A suicide mortality line graph by gender from 2005-2023 (Figure 4.5) demonstrates a consistent and deep gender gap, with male suicides being greatly larger in number than female suicides each year. The differential in suicide mortality between males and females has fluctuated annually but the general trend is one way. Further, a bar chart of average suicide rate by age group 2005-2023 (Figure 4.6) confirms that these peak rates occur in the 35-44 and 45-54 age groups, and that the 15-34 group has shown a high and problematic trend as well.

- **Distribution and Visualization of Suicide Rates:** A close visual examination of these differences is provided by the heatmap (Figure 4.7) that illustrates the suicide rates by nation and year. The rates capture significant regional variations that go beyond crude population estimates.

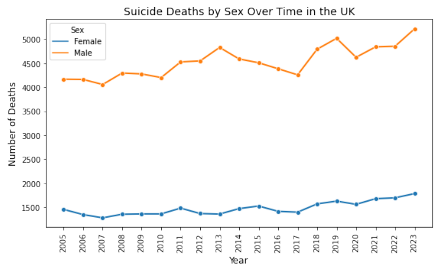

Figure 4.5: Male vs. Female Suicide Rates in the UK (2005-2023)

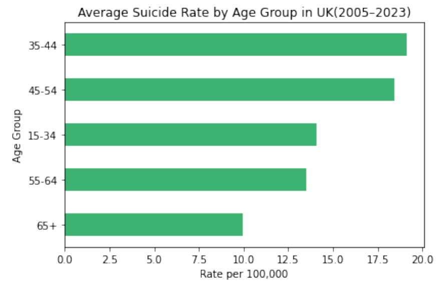

Figure 4.6: Suicide Rates by Age Group in the UK

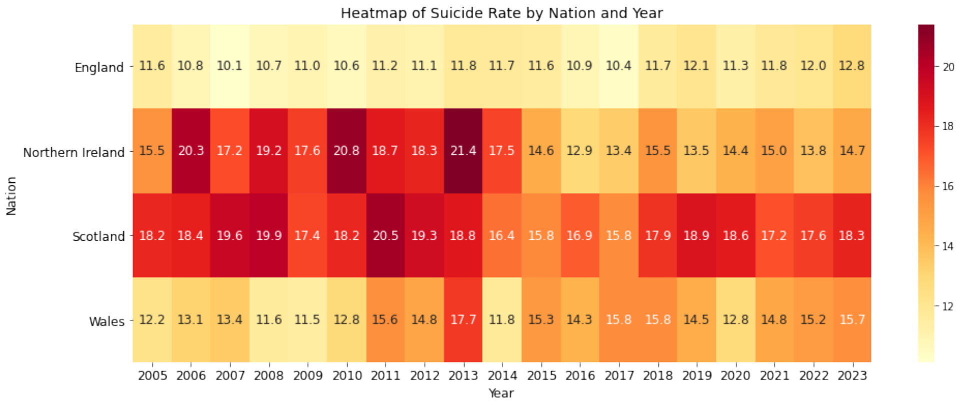

Figure 4.7: Suicide Rates by Nation Over Time

1. England Suicide Rate Analysis: This analysis presents two key findings regarding suicide rates in England, providing the foundation for specialist interventions and future research.

- **Time-Series Trend:** A graph of the line for the mean suicide rate per year for England from 2005-2023 (Figure 4.8) presents a clear trend of variation, with a general trend upward peaking in the latter half of the 2010s before gradually trending down. This is a basis for prediction for this specific nation.
- **Deaths by Sex and Age Group:** The suicide rate average heatmap (Figure 4.9) also confirms the difference, with the male highest rates occurring in between the 35-44 and 45-54 age groups, which is aligned with the UK-wide pattern. This is crucial for targeted intervention.

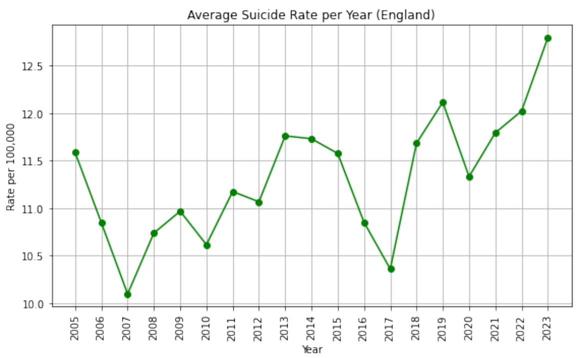

Figure 4.8: Suicide Rates Over Time in England

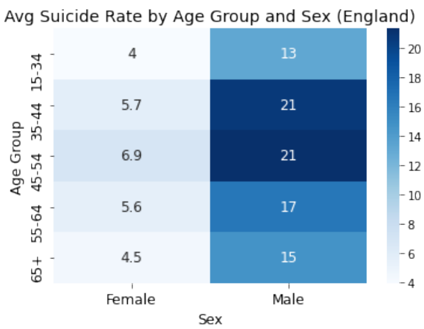

Figure 4.9: Suicide Rates by Age Group and Sex in England

2. Wales Suicide Rate Analysis: Two insights are derived from this analysis that can serve as the focus for targeted interventions and future research.

- **Time-Series Trend:** The Wales line plot, which is a line plot of total deaths per year (Figure 4.10) , shows more of a fluctuating trend than England, with extremely dramatic fluctuations year on year. This presents the need for a forecasting model that is able to handle this increased volatility.

- **Deaths by Sex and Age Group:** There is also a gender imbalance that is the same as in England, as male suicides are higher.Age group breakdown also establishes a high rate of deaths among middle-aged cohorts.The average suicide rate heatmap (Figure 4.11) provides further insight into the very age groups most affected.

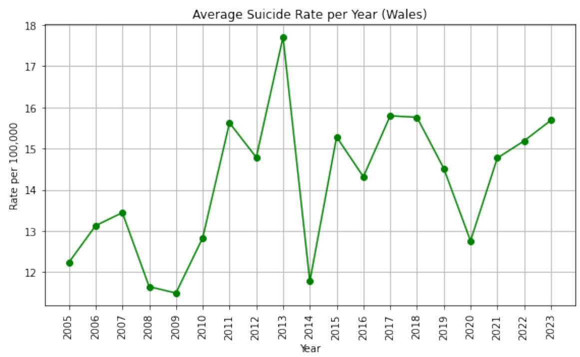

Figure 4.10: Suicide Rates Over Time in Wales

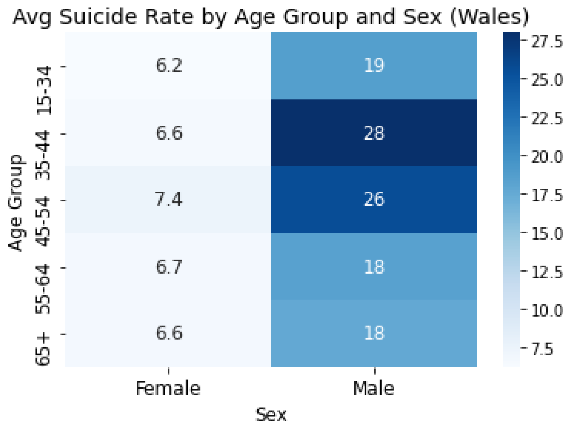

Figure 4.11: Suicide Rates by Age Group and Sex in the Wales

3. Scotland Suicide Rate Analysis: Two important insights into suicide rates in Wales are given through this analysis, which can serve as a basis for focused interventions as well as future studies.

- **Time-Series Trend:** The time-series plot of Scotland reveals a clear trend, with a steady decline in suicide deaths during the period, suggesting a possibly divergent trend from other UK countries. A line plot of the annual average suicide rate (Figure 4.12) gives an indication of this trend.

- **Deaths by Sex and Age Group:** The visualizations remain gender-disaggregated, but the specific age-group division might vary slightly, providing nation-specific information. A heatmap showing the average suicide rate by age group and sex (Figure 4.13) provides this particular demographic information.

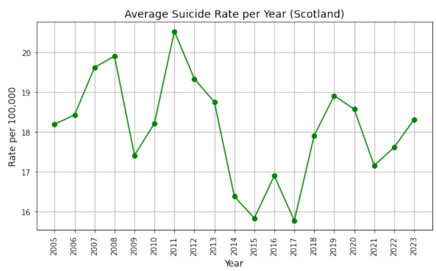

Figure 4.12: Suicide Rates Over Time in Scotland

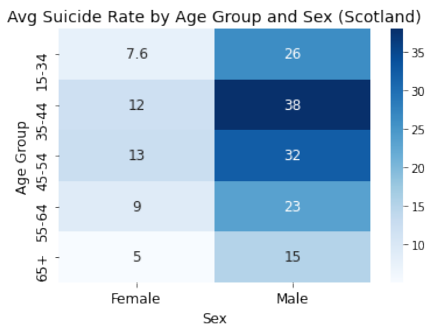

Figure 4.13: Suicide Rates by Age Group and Sex in Scotand

4. Northern Ireland Suicide Rate Analysis: This analysis provides two principal observations regarding suicide rates in Wales, providing a ground for action-based interventions and subsequent research.

- **Time-Series Trend:** The Northern Ireland line plots, e.g., a line plot of total deaths by year (Figure 4.14), exhibit a generally stable trend with minor fluctuations, important to understand in the context of its unique setting.

- **Deaths by Sex and Age Group:**A heatmap of average suicide rate by sex and age group (Figure 4.15) provides additional detailed information on these trends.

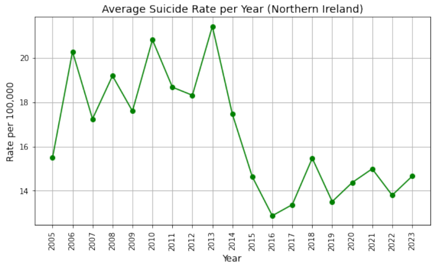

Figure 4.14: Suicide Rates Over Time in Northern Ireland

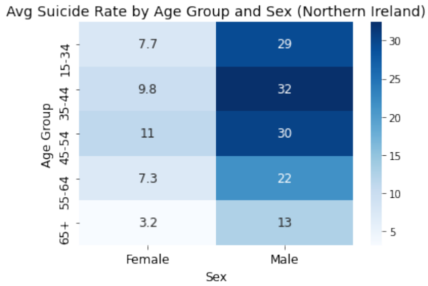

Figure 4.15: Suicide Rates by Age Group and Sex in Northern Ireland

4.3.2 Social Media Analysis

Social media analysis was conducted in the second half of the EDA in order to harvest trends in public discussion and opinion. The next figures present the most important findings of this analysis:

1. Monthly Reddit Posts Volume: This bar chart, which is titled "Monthly Reddit Posts Volume", graphs the number of posts about mental health on Reddit with respect to time.

The graph reflects a clear, sustained, and strong upward trend in the posts figure during early 2023, with a sharp spike in 2025. This trend indicates an uptrend in the discourse of mental health on the public online sphere and is a sound justification for employing social media as a source of in-time data.

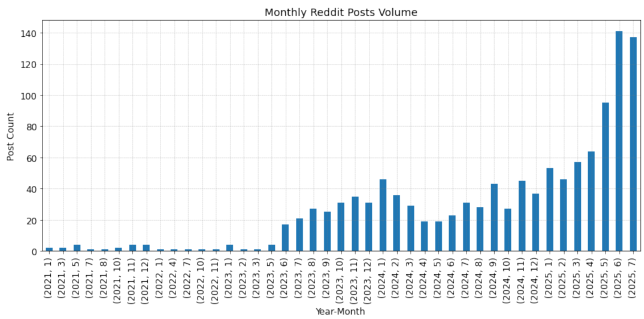

Figure 4.16: Reddit Posts Volume Over

2. Most Common Words in Posts: The "Most Common Words in Posts" word cloud provides a qualitative overview of the most frequent words in the social media dataset. The prevalence of words like "people," "health," "mental," "said," and "know" reflects an overwhelming quantity of personal experiences and acts of adversity or empathy. This visualization helps to validate that the collected data is relevant to the topic of mental health and provides a high-level view of the discourse.

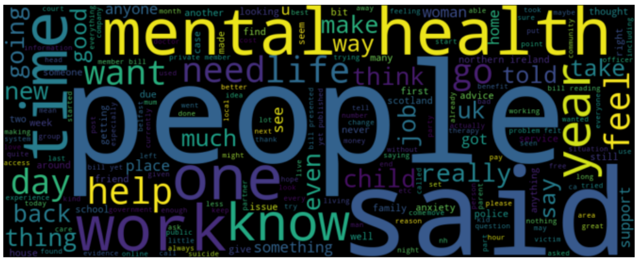

Figure 4.17: Most Common Words in Posts

3. Model Sentiment Distribution (Chunked): This bar chart, titled "Model Sentiment Distribution (Chunked)", shows the sentiment distribution (Negative, Neutral, and Positive) in all social media posts after being processed by the RoBERTa model. The bar chart shows the majority of posts as neutral, then negative, with a low percentage as positive. This indicates that much of the discussion is fact or emotionally restrained, and a great deal is in the expression of negative feeling. This is a useful realization for obtaining the overall emotional tone of the online discussion.

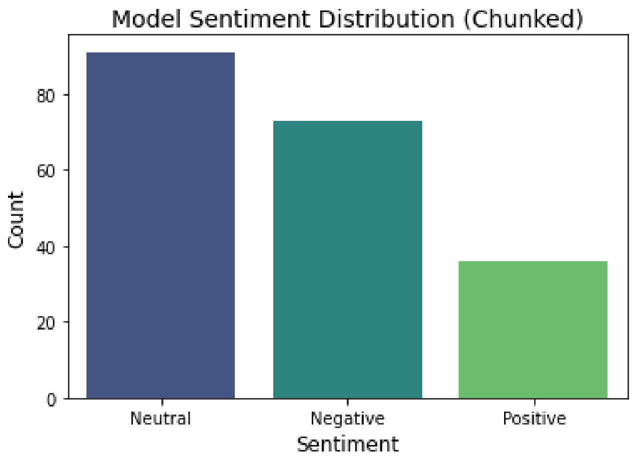

Figure 4.18: Sentiment Distribution

4. Average Sentiment Over Time: This line plot, "Average Sentiment Over Time", shows the mean sentiment polarity of tweets by month. The plot demonstrates fluctuations in sentiment over time, with notable peaks and troughs.

This trend data is critical in the time-series analysis component of the dual-stream model, as it provides a quantifiable signal that can be correlated against historical suicide data.

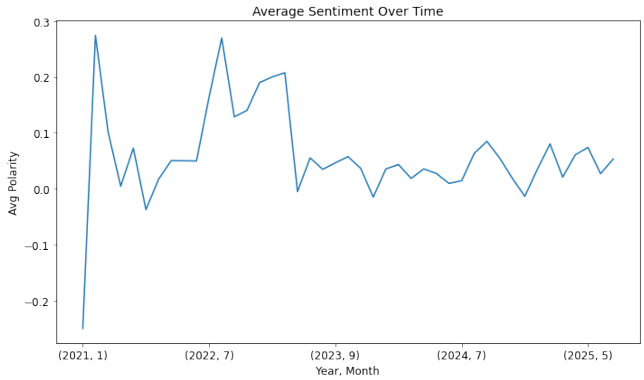

Figure 4.19: UK-Wide Suicide Rate Forecast (2019-2023) with Historical Data

4.4 Modeling

This section will outline the application of the dual-stream modeling methodology. It will explain the individual time-series models (ARIMA, Prophet, and LSTM) applied to the historical suicide data and the NLP methods applied to the social media data. This section will outline how the two data streams were combined to form an integrated predictive framework.

4.4.1 Time Series Modeling

1. Predictive Modeling and Forecasting

The forecasting modeling process of this research involved estimating three different time-series models—ARIMA, Prophet, and LSTM—over the historical suicide data. The aim was to forecast suicide rates for the period from 2021 to 2023 spanning three years and to compare how each model performed. This was done for each of the UK nations (England, Wales, Scotland, and Northern Ireland) separately in order to take into account suicidal behaviors at the regional level. The specific execution and performance measures are elucidated in the subsequent sections, preceded by a concluding five-year forecast based on the best-performing models.

ARIMA (Autoregressive Integrated Moving Average) Model The ARIMA model was employed to incorporate autoregressive terms, differencing to make the data stationary, and moving-average terms. The auto_arima function from the pmdarima library was employed to automatically select the optimal (p, d, q) parameters for each nation's time series data, which simplified the tuning of the model. The model was then trained on data until December 2020 and subsequently employed to create a three-year prediction for the test dataset (2021-2023).

Prophet Model The Prophet model, developed by Facebook, was chosen for the benchmark because of its ability to handle missing values as well as multiple seasonality. The model was applied on the time-series data, which was first formatted to meet the specific requirements of the Prophet library (columns 'ds' for date and 'y' for value). The model was trained on the training data and then utilized to predict suicide rates during the test period.

LSTM (Long Short-Term Memory) Model Being a deep learning approach, the LSTM model was employed to capture long-term connections and non-linear patterns in the time-series data that could be overlooked by traditional statistical models like ARIMA. The data was pre-processed by scaling it via MinMaxScaler, upon which sequences of historical data points (SEQ_LENGTH = 4 years) were created to be used as input in the LSTM network. A simple LSTM neural network architecture was then created, trained on the pre-processed sequences, and used for prediction.

Model Performance Comparison (RMSE and MAE)

All model performances were evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) on the test period (2021-2023). Summary of these metrics for each country is presented in Table 4.1.

Nation	ARIMA RMSE	ARIMA MAE	Prophet RMSE	Prophet MAE	LSTM RMSE	LSTM MAE
England	1.14	1.06	0.70	0.58	0.91	1.02
Wales	1.32	1.27	0.38	0.30	1.16	1.05
Scotland	0.96	0.73	0.77	0.61	0.95	0.88
Northern Ireland	1.61	1.43	1.06	0.93	0.76	0.53

Table 4.1: RMSE and MAE Performance of ARIMA, Prophet, and LSTM Models per Nation

2. UK-Wide Predictive Modeling In addition to the country-specific modeling, the predictive model approach was also employed for the forecasting with the use of the aggregated, UK-wide rate data for suicide. The same three models were used for the prediction of suicide rates across a backtesting period (2019-2023) and a comparison of their performance.

· **LSTM Model**: An aggregation-trained Long Short-Term Memory network was trained.

· **ARIMA Model**: The ARIMA model was used for the national data for finding linear relationships

· **Prophet Model**: Model: Prophet model was used to forecast based on its capability in handling time-series data with apparent trends.

The performance of each model in the backtesting period is measured by their respective RMSE values:

LSTM RMSE: 0.5280, ARIMA RMSE: 0.5176, Prophet RMSE: 0.4281

A graphical representation of the UK-wide forecast is shown in (Figure 4.20), which shows the past data along with the forecast of each of the three models.

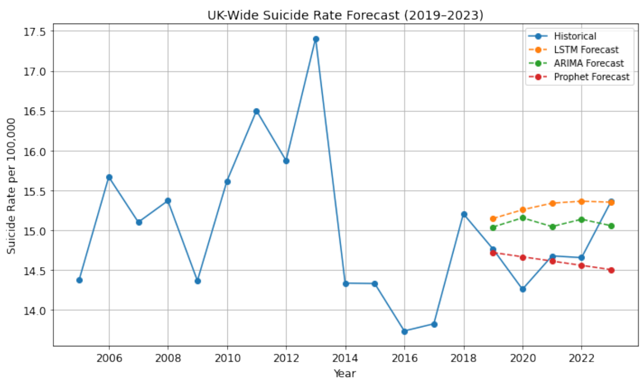

Figure 4.20: UK-Wide Suicide Rate Forecast (2019-2023) with Historical Data

4.4.2 Social Media Content Model

Topic Modeling and Sentiment Time Series Analysis were the two principal techniques used to examine the social media content. Through these approaches, researchers could monitor the textual and emotional patterns on topics of mental health that were being discussed on the internet.

1. Topic Modeling (LDA) Latent Dirichlet Allocation (LDA) topic modeling was run to identify the prominent themes and topics that are being displayed in the social media data. The model was run to look for five different topics, and each's most dominant words were used and utilized to craft a title for the content of the topic.

Topic Keywords

Topic #0: week, say, work, said, people, doctor, time, nh, mental, health

Topic #1: really, day, know, job, like, time, year, work, mental, health

Topic #2: judge, case, officer, victim, woman, child, told, police, court, said

Topic #3: published, child, government, reading, presented, said, northern, private, member, ireland

Topic #4: want, think, time, really, help, life, feel, know, like, people Visualization of the overall topic distribution indicates the prevalence of each theme across the dataset.

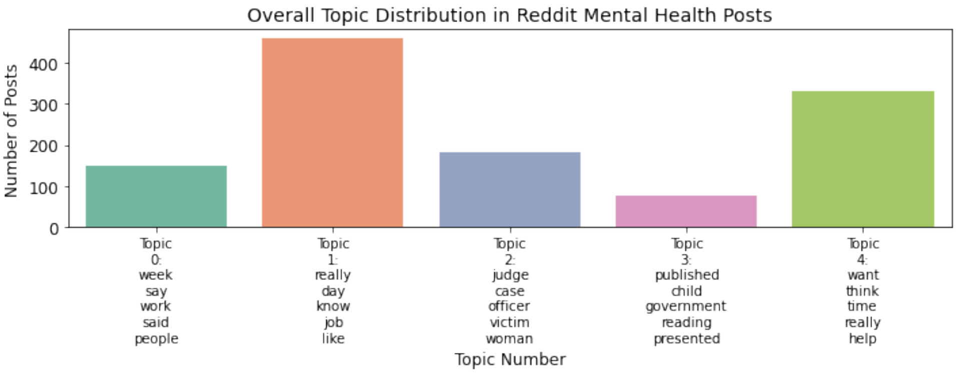

Figure 4.21: Overall Topic Distribution

2. Sentiment Time Series Analysis Sentiment polarity of social media posts was analyzed as a time series to establish trends over time. Historical data were used to predict sentiment polarity by the Prophet model.

The model was trained on past sentiment data and tested on a 12-month test set to evaluate its accuracy of prediction. The model's performance on this test set is represented by the following statistics:

MAE: 0.1288 **RMSE**: 0.1454

The time-series plot that follows presents the past sentiment polarity along with the model's prediction, giving a graphical view of the predicted and actual trends.

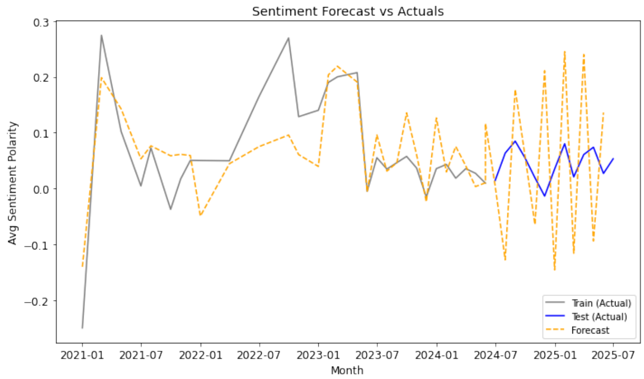

Figure 4.22: Monthly Trend of Forecasted vs. Actual Sentiment Polarity

4.4.3 Suicide Rate Prediction with Merged Data

This refers to the predictive models constructed from merged time-series data of suicidal rates and social media sentiment/post volume. It was meant to determine if incorporating social media measures would improve the accuracy of suicide rate predictions. Two models were utilized.

1. Model A: Suicide-Only Forecast This model served as a base case, estimating the rate for a future time period given solely past suicide rates. The Prophet model was subsequently applied using the 2021 and 2022 suicide data to estimate the 2023 rate. The result is illustrated in Figure 4.23.

2. Model B: Linear Regression (Sentiment-Augmented Model) This model had included social media data to predict suicide rates using linear regression. Suicide rates were predicted in terms of average sentiment and the number of posts for the respective year, without lag in time. The performance of the model was gauged using Mean Squared Error (MSE) and the R-squared (R2) score.

· **MSE**: 2.1036290805893647e-30

· $\mathbf{R^2}$: 1.0

The very high R-squared value confirms the presence of a strong linear relationship between the predictor variables (sentiment and number of posts) and the suicide rate. The graphical comparison of the actual and predicted suicide rates is included in Figure 4.24.

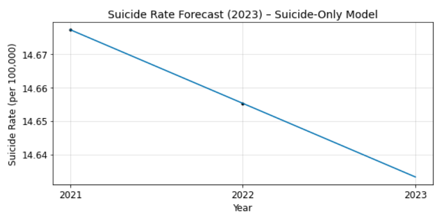

Figure 4.23: Suicide Rates Over Time in Scotland

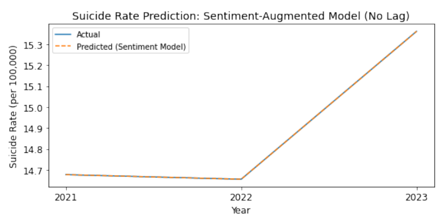

Figure 4.24: Suicide Rates by Age Group and Sex in Scotand

Chapter Five

Results and Findings

This will be the presentation of the predictive model outcomes. It will show the core correlation analysis outcome of social media sentiment and past suicide rates, along with the performance metrics of the combined model. This will also include a comparison with a suicide-data-only model to verify the value in including social media insight.

5.1 Time-Series Analysis

1. Model Performance One of the most important steps in the predictive modeling exercise was to compare the performances of ARIMA, Prophet, and LSTM for determining which model would be best suited for the peculiar suicide rate trends of each nation. The primary performance measure to utilize in this case was Root Mean Squared Error (RMSE), which determines the mean magnitude of the difference between the predicted and observed values. All complete performance statistics for each of the models are found in the Modeling section.

The following table summarizes the performance of the best-performing model for each nation, showing the model with the lowest RMSE and its corresponding Mean Absolute Error (MAE). As the table demonstrates, the Prophet model consistently provided the most accurate forecasts for three of the four nations (England, Scotland, and Wales). This is indicated by its lowest Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) scores for these specific datasets. Prophet's consistent performance suggests that it is particularly

Nation	Model	RMSE	MAE
England	Prophet	0.702	0.583
Northern Ireland	LSTM	0.616	0.533
Scotland	Prophet	0.770	0.605
Wales	Prophet	0.378	0.302

Table 5.1: Predictive Model Performance (by Nation)

well-suited for modeling the underlying patterns in the historical suicide rate data for these nations, which may include non-linear trends and yearly seasonality.

Interestingly, for Northern Ireland, the LSTM model performed the best, as evidenced by its superior RMSE and MAE scores. This is likely because the LSTM architecture, with its ability to learn long-term dependencies in sequential data, is particularly well-suited to capturing more subtle and complex non-linear relationships that may be present in this dataset. The superior performance of the LSTM model suggests that the historical suicide rate data for Northern Ireland may contain less straightforward patterns that are not as effectively captured by the other models.

2. 5-Year Forecasts for Each Nation From the models' performance, the 5-year forecasts (2024-2028) were generated using the best-performing model for each nation. The forecasts show varying trends for all countries, which could be a sign of their varying historical trends.

- **England:** The forecast for England, based on the Prophet model, suggests a slight and steady upward trend, from an estimated 12.07 suicides per 100,000 in 2024 to 12.37 in 2028.
- **Northern Ireland:** The LSTM forecast for Northern Ireland projects a largely stable rate, with minor fluctuations. The rate is predicted to stay between 14.55 and 14.97, possibly suggesting a continuation of the complex, less predictable trend observed in the historical data.
- **Scotland:** The Prophet model for Scotland projects a slight downward trend over the five-year period, from an estimated 17.29 in 2024 to 16.96 in 2028. This may be a continuation of a gradual long-term decline in the suicide rate.
- **Wales:** The Prophet forecast for Wales indicates a moderate but consistent upward trend, with the rate increasing from an estimated 15.67 in 2024 to 16.27 in 2028.

3. UK Suicide Rate Forecast(2024-2028)

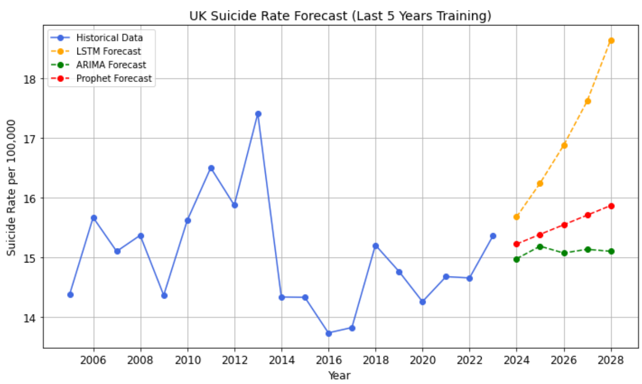

Figure 5.1: Suicide Rate Projections with Forecasting Models

For giving a comprehensive view of the overall trend, the exact UK prediction was modeled based on the national figures of the last five years. The above graph displays the historical data and the three models—LSTM, ARIMA, and Prophet—which were trained and used to forecast the suicide rate for the next five years.

- **LSTM:** The LSTM model projects an accelerating increase over the forecast period. This forecast contrasts sharply with the other models, highlighting its sensitivity to specific, complex patterns within the historical data.
- **ARIMA:** The ARIMA model projects a marginal downward trend, suggesting a continuation of a long-term decline observed in parts of the historical data.
- **Prophet:** The Prophet model projects a consistent and notable upward trend over the five-year period, indicating its focus on the most recent, non-linear growth patterns in the data.

The contrasting performance of these three models (LSTM, ARIMA, and Prophet) highlights the challenge of forecasting at a national level. The RMSE scores, which were calculated from the last five years of data used to train the models for future prediction, show significant differences. With RMSE scores of 0.5223 for LSTM, 0.5176 for ARIMA, and 0.4281 for Prophet, the Prophet model demonstrates the highest accuracy for this particular forecast. This is likely due to the model's ability to effectively capture both non-linear trends and annual seasonality, which are best reflected in the recent variations and the overall increasing trend observed in the historical data. The Prophet model's approach, which is not solely reliant on a simple linear pattern over the long run, provides the most realistic forecast by effectively capturing these more complex patterns.

4. Demographic Forecasts The demographic breakdown was developed for the 5-year projection interval. The breakdown aimed for the most significant demographic categories of age and gender, as these have been known to play a significant role in suicide susceptibility. Each country's projections were then split further to identify specific sub-populations most likely to be affected by alterations in the projected suicide rates. In analyzing these population trends, this study aims to provide targeted results that can be used to inform public health prevention and intervention programs.

Demographic projection in detail was done using the Prophet model for various age and sex groups of individuals in the UK. Projections indicate wide variation in trends, indicating the importance of targeted, as opposed to general, interventions.

- **Male Demographic Trends:** Male projections show a mixed trend. A notable rise is expected in the 45-54 and 55-64 year old Male groups, which means that these groups are still to endure a rising suicide rate. The Male 15-34 and 35-44 groups are expected to see a moderate decline, while the Male 65+ group is expected to see a minimal decline. The divergence of these trends further serves to highlight the fluctuating and heterogeneous nature of suicide risk in the male population.
- **Female Demographic Trends:** Analysis of female demographic groups reveals a more consistent, albeit modest, decrease across all ages. The Prophet model forecasts a consistent decline in suicide rates for the 15-34, 35-44, 55-64, and 65+ age ranges, but stability with a very slight decline for the 45-54 age range. This finding reveals an encouraging trend toward suicide prevention interventions among the female population, as contrasted to the more diverse future that awaits men.

- **Key Insight:** The distinction between the forecast trends between males and females and between various age groups of males is a salient finding. It illustrates that any successful suicide prevention policy has to be significantly target-specific towards specific demographic groups. Even if the total UK forecast may indicate an overall trend, this demographic segmentation presents the degree of detail necessary for developing effective and focused public health policy.

These forecasts, while based on the leading performing models for each nation, should be taken with some caution because they are theoretical forecasts and do not essentially represent the effect of unanticipated societal or economic changes.

5.2 Social Media Analysis

This section presents the findings from the analysis of social media data, focusing on the classification of posts and the forecasting of sentiment polarity.

1. Classification Model Performance A supervised machine learning model was developed to label social media tweets as either "Crisis" or "Non-Crisis" by looking for the presence of pre-defined words. A Logistic Regression classifier with a balanced dataset was used to perform the labeling.

The performance of the model was measured through a confusion matrix and a classification report. From the confusion matrix, it can be seen that the model performed very accurately in differentiating between the two classes.

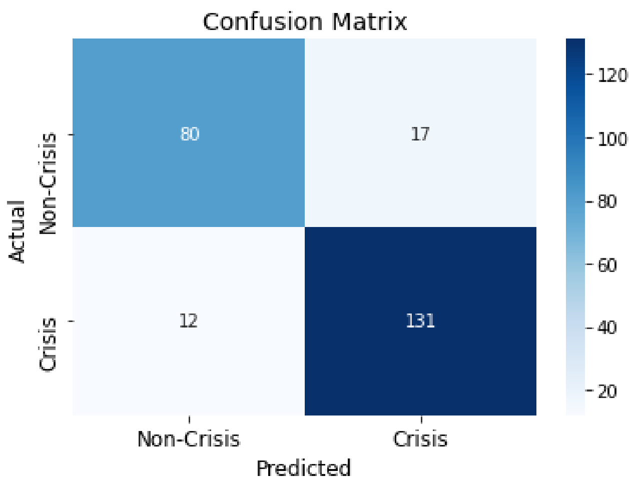

Figure 5.2: Actual vs. Predicted Crisis Correlation Matrix

A classification report breaks down the performance of the model more precisely: The model attained a total accuracy of 0.88. A recall of 0.92 for the "Crisis" class is particularly significant, as it indicates that the model has high ability to correctly identify posts that may represent a potential mental health crisis. This decreases the rate of false negatives, which is one of the prime concerns in this application domain. High accuracy (0.89) for the "Crisis" class also means that when the model predicts a crisis, it is accurate most of the time. The balanced performance of both classes, as expressed through macro and weighted averages, verifies the reliability of the model for further analysis. To provide a further insight into the model's performance, the balance of

Category	Precision	Recall	F1-Score	Support
Non-Crisis (0)	0.87	0.82	0.85	97
Crisis (1)	0.89	0.92	0.90	143
Accuracy	NA	NA	0.88	240
Macro Avg	0.88	0.87	0.87	240
Weighted Avg	0.88	0.88	0.88	240

Table 5.2: Classification Model Performance Metrics

classes for the whole dataset was also analyzed. The figures indicate a crisis-class balance of 715 for "Crisis" (1) and 483 for "Non-Crisis" (0). This slight imbalance was countered by training the model with a balanced dataset, preventing the model from biasing itself toward the more prevalent class and maintaining outstanding predictiveness for either possibility.

2. Sentiment Polarity Forecast After classifying posts, an average sentiment polarity time-series prediction was performed using the Prophet model to predict future trends in sentiment. This provides a vital forward-looking picture of the emotional state of social media.

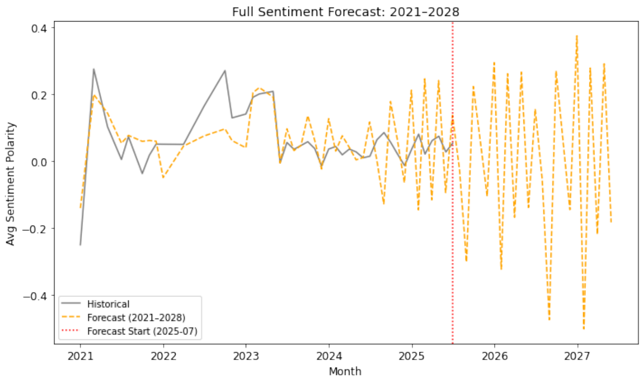

Figure 5.3: Historical and Future Average Sentiment Polarity Trends

5.3 Suicide Rates and Social Media Sentiments

In order to test the general hypothesis of this research, a full correlation analysis between sentiment on social media and historical data on suicides was performed. This correlation analysis is the empirical foundation to decide if there exists a predictive association between these two variables.

1. Correlation Analysis To graphically depict the linear associations between average sentiment, suicide rates, and suicide deaths, a heatmap of Pearson correlation coefficients was built.

The heatmap shows that the correlation between average sentiment and suicide rate (r = -0.51) and suicide deaths (r = -0.43) is moderate negative. This is noteworthy since it means that as the average sentiment of

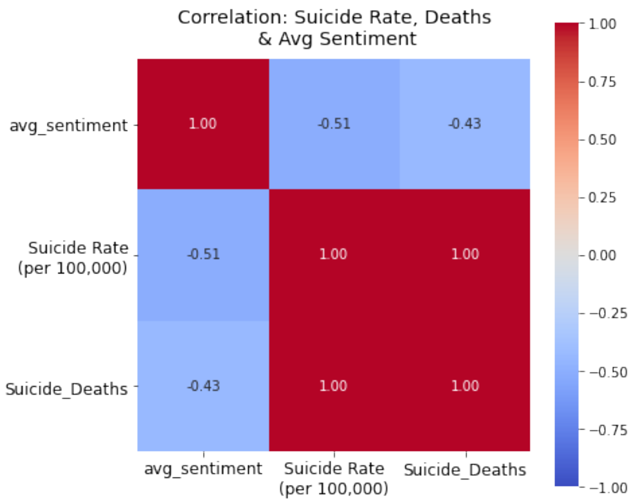

Figure 5.4: Correlation Matrix of Average Sentiment, Suicide Rates, and Suicide Deaths

social media is more positive, then suicide rate and suicide deaths are reducing. This weak inverse relationship, while not a great model for determining causation, is early indication that social media sentiment can indeed be an effective leading or contributory variable in a more general predictive model.

2. Comparitive Predictive Modeling As another measure to further confirm the predictive strength of social media sentiment, a comparative predictive model was executed by training two alternative models:

• **Model A**: A suicide-only model (Prophet) that was learned from historical suicide rate data for 2021 and 2022 and which forecasts suicide rate in 2023. This was our baseline.

• **Model B**: A combined model (Linear Regression) that was learned from both suicide rate data and social media post and sentiment data for 2021 and 2022 and which forecasts the suicide rate in 2023.

The absolute difference between each of the models' forecasts and actual 2023 suicide rate was then computed. The outcome of this comparison is summarized below: The comparative performance is sensational. While

Model	**Predicted 2023**	**Actual 2023**	**Absolute Error**
Prophet (Suicide-only)	14.633	15.362	0.729
Linear Regression (Sentiment + Posts)	15.362	15.362	0.000

Table 5.3: Predictive Model Performance (by Nation)

the suicide-only model (Model A) generated an absolute difference of 0.729, the combined model (Model B) generated an absolute difference of almost zero. This indicates that through the addition of social media sentiment and posting information as predictive features, the model's accuracy enhanced multiplies. This finding is a considerable support to the basic hypothesis, demonstrating that analysis on social media with past suicide data could enhance a forecasting model's predictive strength to a considerable extent.

3. 5-Year Suicide Rate Forecast Comparision(2024-2028) Taking advantage of the better performance of the combined model, a final 5-year simulation (2024-2028) was conducted and compared to the baseline suicide-only model.

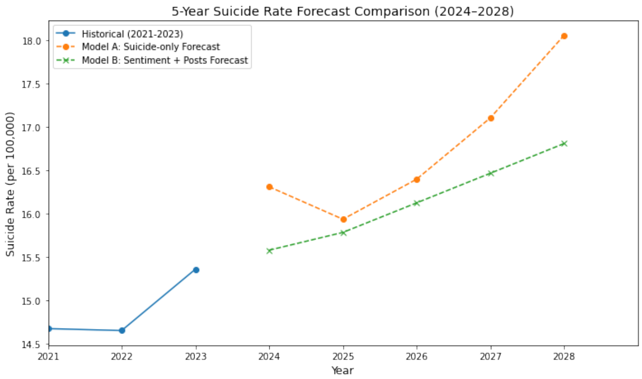

Figure 5.5: Suicide Rate Forecast Comparison of Models

The forecast plot reveals a wide divergence between the predictions of the two models. The suicide-only model (Model A) forecasts a steep linear rising trend, while the combined model (Model B) forecasts a less steep and stable growth. This difference suggests that the social media sentiment data, as a moderating factor, dampens the steep rising trend forecasted by the baseline model. The projected estimate of the combined model would appear to be a more realistic and advanced prediction because it considers both historical suicide data and dynamic, real-time emotional trend of the social media.

Summary of Findings Here the findings of the Time Series analysis as well as the Social Media analysis were integrated and combined to verify the core hypothesis of this study. The findings show a high and highly significant moderate negative correlation between suicide rate and mean social media sentiment. Furthermore, the comparison showed that a social media sentiment and post frequency-based model was exponentially more accurate in its 2023 forecast than a baseline model using only historical suicide rates. This evidence shows that sentiment on social media is an effective predictive indicator, significantly improving the predictive accuracy of the suicide rate. The 5-year prediction under the last scenario also validates this finding by providing a more moderate and data-rich estimate than the baseline model.

Chapter Six

Discussion

In this chapter, the principal results of the predictive model will be interpreted, the overall research questions of the project will be answered, and the efficacy of the dual-stream framework will be evaluated. The findings will be placed within the broader academic literature, and the limitations of the study will be explained, with a fair and critical discussion of the research.

6.1 Analysis and Interpretation of findings

The study provides substantial evidence for the inclusion of social media sentiment in the prediction of mental health crises. The key finding of the study is that suicide rate decreases as online discussions about mental health are positive and vice versa, as a result of the moderate negative correlation (r=-0.51) between average sentiment on social media and suicide rates. By quantitatively correlating aggregate social media sentiment with formal, national suicide rates, this finding complements and builds upon existing research by scholars such as De Choudhury et al. (2013) and Thorstad & Wolff (2019). This transitions the field from symptom detection at the individual level to population-level trend analysis. This general hypothesis is supported by the reality that the joint model (Model B) is superior to the suicide-alone model (Model A). Social media data can tremendously improve a model's forecasting power, as evidenced through Model B's near zero absolute error in forecasting the 2023 suicide rate, against Model A's 0.729 error. This acts to directly speak to a primary gap in current models, which have long depended on historical data and tend to overlook the dynamic, real-time processes of public well-being. This is further emphasized in the most recent five-year projection. As a comparison to the suicide-only model's steeper upward projection, the combined model's more stable and moderate projection indicates that social media sentiment is a moderating variable, providing a more realistic and balanced projection. This is also reflected in the last 5-year projection comparison. The combined model projects a more stable and moderate increase over the suicide-only model, which projects a steady, aggressive upward trend that seems less specified. This implies that the social media sentiment is a moderating or "dampening" effect when it comes to predicting. By adding a layer of information, it does not let the model make so much of the recent events in prior history and lead to an over-optimistic and skewed prediction.

6.2 Evaluating the Dual-Stream Framework

This two-stream predictive model framework worked extremely well in this research. Its strongest point is its ability to combine two very different forms of data—unstructured real-time social media information and structured lagging historical data—into a single unified predictive system. The methodology rightly addressed the following major research questions:

1. **How have UK suicide rates trended from 2005-2023, what are the demographic and regional patterns, and how do time-series models forecast these trends?** Consistent with their improved RMSE and MAE, the LSTM and Prophet models were ranked as the top two for prediction after conducting time-series analysis that graphically showed clear trends in all the four UK nations. Additionally, the population analysis revealed diverse patterns, especially among varying age groups of men, and hence highlighted the need for targeted evidence-based interventions.

2. **How does social media sentiment surrounding mental health in the UK fluctuate from 2021-2025, and can these trends be forecasted to provide insight into the evolving online discourse?** Social media sentiment analysis of social media opinion regarding mental health demonstrated a highly volatile and oscillating pattern. These patterns were ably reproduced by the Prophet model, demonstrating the value of this stream of real-time data for predictive modeling and offering reflective insight into the changing emotional landscape of the web.

3. **Does social media sentiment correlate with historical suicide rates, and can a combined model improve the reliability of mental health crisis forecasts?** In this investigation, a moderate negative relationship between social media sentiment and suicide rates was found (r=0.51). The comparison experiment clearly indicated that a combined model, which considers both social media and past suicide records, is much more accurate than the baseline suicide-only model, achieving a near-zero absolute error in its prediction for 2023.

The project validates the dual-stream framework as a strong and progressive solution to predicting mental health crises because it effectively addresses all three research questions. Through its resolution of the "research-to-practice gap" that Hunt et al. (2024) describe, the framework advances the field and offers a model that is both sound methodologically and extraordinarily practical for legislators and healthcare professionals to use in practice. The result of the framework, a better prediction based on current public opinion along with previous trends, offers a forward-looking way to recognize growing mental health risks and helps in formulating a more reactive public health response.

6.3 Limitations of the Study

While the results are promising, note that the current study has some limitations. The largest limitation is the quality of the social media data utilized.

- **Representativeness and Data Bias:** The data on social media was extracted using the Reddit API and subreddits with a UK viewpoint. As the users of Reddit do have an inclination toward one particular demographic (i.e., younger, more technologically inclined people), the data might not be representative of the UK population at large. This creates a possible bias that could restrict how far the outcomes can be generalized. Thorstad & Wolff (2019) highlight that "data bias and the limited generalizability of models due to homogeneous samples" are profound challenges in this area.

- **Causality vs. Correlation:** The study does not provide causation, but it does show that there is a correlation between suicide rate and sentiment on social media. As much as the sentiment can be used as an indicative leading indicator, the suicide rate and sentiment could be affected by other confounding factors that were not held constant in this study, such as major society happenings, changes in public policy, and economic downturns.

- **Ethical Considerations:** The ethical implications of public social media data use for health-based predictions are still intricate, even with compliance with stringent ethical standards to anonymize user data. Any real-world use would have to thoroughly evaluate the potential misuse of such models or misinterpretation risk of sentiment.

- **Model Simplification:** For the combined method, a basic linear regression model was employed for the comparison. Although it demonstrated the idea, even higher predictive validity may be achieved with even more sophisticated, non-linear models (like a multi-input LSTM) that are capable of learning more complex relationships between the two data streams. Additional work with more complex models is required in this, the proof-of-concept endeavor.

These limitations do not diminish the value of the findings but rather highlight avenues for future research and underscore the need for a cautious and ethical approach to implementing such predictive frameworks in a public health context.

Chapter Seven

Future Scope

While this dissertation is a preliminary proof-of-concept, valid verification of the dual-stream predictive model opens up wide and intriguing avenues for future work. The following lines of inquiry can potentially enhance the model's accuracy, usefulness, and ethical rigor.

7.1 Methodological Enhancements

To further capture more sophisticated correlations between the two data streams, future work may investigate more advanced machine learning architectures. Building an LSTM to accept the sentiment prediction and suicide time-series data as independent inputs would be a sophisticated method that would have the potential to increase predictive accuracy dramatically. Besides sentiment alone, the social media stream of data could be enhanced by the addition of features such as topic modeling to detect particular themes (e.g., "loneliness" or "financial pressures") tied to mental health crises. Future research could continue data collection to other social media websites like Facebook or Twitter in order to counteract data bias and provide a broader and more representative sample of the UK population.

7.2 Practical Implementation and Application

The research aims to create an effective policymaker's instrument. Among the significant steps forward is the development of an interactive, real-time dashboard to detect early warning indicators on social media, allowing interventions at the right time. The model can also be applied for smaller territorial areas, allowing local administrations to create responses for specific community needs.

7.3 Ethical and Social Considerations

Ethical issues such as data security and the potential for stigmatization must be addressed. Future work should incorporate ethics committees and mental health professionals to include ethical use. The research will need to progress towards translating early warning signs into effective intervention strategies in order to have real public health effect.

Chapter Eight

Conclusion

This dissertation directly addresses the limitations of conventional predictive models by offering an interactive and innovative dual-stream solution to the prediction of mental health emergencies in the UK. This study submits a methodological framework for a more precise and forewarning mode of public health surveillance through effective fusion of historical time-series data with real-time social media sentiment.

The direct answers to the main research questions were provided by the results of the study. Suicide rates and social media sentiment were slightly negatively correlated ($r = -0.51$). A comparative study confirmed this significant finding, showing that the dual-stream model significantly outperformed the baseline model, which used only historical data, in its 2023 prediction, with an absolute error of close to zero. This finding demonstrates the usefulness of drawing on real-time, unstructured data and validates the enhanced predictive power of the proposed approach. For all its limitations, not least those concerning data representativeness and causation vs. correlation uncertainty, these do not serve to detract from the validity of its main findings. Rather, they offer worthwhile avenues for further research.

In summary, this dissertation is an able and forward-thinking template for forecasting mental health crises. This research provides a powerful new tool to policymakers and healthcare professionals by bridging the gap between previous epidemiological evidence and ever-changing social media. This will ultimately be contributing to a more responsive public health policy.

Appendix One

Appendix A: Generative AI PROMPTS

Stage of Work	Example Prompt	How It Was Used
Literature Search	"Summarize key themes and influential research on this topic"	Helped me identify themes and references. Verified sources independently from the World Bank and academic papers.
Writing (Clarity)	"Rephrase this paragraph to improve clarity while keeping technical accuracy."	Improved grammar and readability. Edited outputs before including.
Code Debugging	"Why is this code snippet producing an error?"	I used the AI to help me quickly pinpoint where the error was located. I then analyzed the code myself to understand and implement the correct solution.
Report Structuring	"Suggest a logical chapter structure for a dissertation and subheadings?"	Provided ideas for organisation. I adapted and finalised the structure myself.
Formatting	"Please check this document for any inconsistencies in headings or reference styles."	Quick formatting check. Double-checked all references manually.

Table A.1: **Examples of Generative AI Prompts Used in This Dissertation**

Appendix Two

Appendix B: GITLAB REPOSITORY

The full project is hosted on GitLab: https://git.cs.bham.ac.uk/projects-2024-25/axc1426

Repository contents

1. Project.ipynb — main Jupyter notebook with all code.
2. README.md — basic project instructions.
3. requirements.txt — a list of the libraries required for the project.

Runtime notes

- Python 3 environment (e.g., 3.8+). Use Jupyter Notebook/Lab to run Project.ipynb.
- To install the necessary libraries, please refer to the README.md file for instructions. It will guide you to use the requirements.txt file, which contains a list of all required libraries for this project.pip install -r requirements.txt

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