BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE & ENGINEERING DEPARTMENT OF COMPUTER SCIENCE

SUICIDE DETECTION SYSTEM

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TOPIC: ASSESSING TEXT INPUT FROM TELEGRAM FOR EARLY SUICIDE RISK DETECTION

APPROVAL FORM

The undersigned certify that this dissertation, prepared by Elton Mutete (B210727A), entitled "ASSESSING TEXT INPUT FROM TELEGRAM FOR EARLY SUICIDE RISK DETECTION" meets the requirements for the Bachelor of Science Honors Degree in Computer Science at Bindura University of Science Education.

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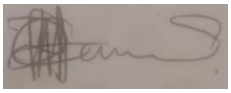
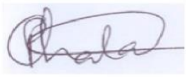
SUPERVISOR:  DATE: 03/08/2025

CHAIRPERSON:  DATE: 03/08/2025

DEDICATION

This research is in remembrance of all those silently struggling with mental health concerns, whose unseen battles motivated this research. I also dedicate this to the mental health practitioners working under adverse conditions in poor-resource settings with minimal tools at their disposal. Finally, I dedicate this to my family members, whose unwavering emotional support and resilience granted the psychological fortitude required to accomplish this academic journey through both challenging and triumphant moments.

DECLARATION

I hereby declare that this thesis is my own original research work and has not been offered for any other academic award. All research techniques, data analysis, and results concluded in it were done by me unless otherwise indicated specifically quoted. I have appropriately credited all reference texts, published papers, and collaborative work in due academic citation. This research strictly adhered to the ethical guidelines for artificial intelligence application in mental wellness as adopted by the institutional review board. The rollout maintained high levels of privacy, anonymous handling of all user data and no long-term storage of sensitive information.

ABSRACT

This work addresses the central world problem of suicide prevention by leveraging innovative artificial intelligence methods, emphasizing the crossing cultural and language gaps in low-resource settings. The research constructed and evaluated a multilingual suicide risk evaluation system grounded on AfriBERTa architecture, optimized for a specially prepared dataset of 15,000 labeled English posts across mental health forums and professionally certified Shona translations. The system was accurate to 88.11% in classification and stable across risk categories and performed particularly well in detecting culturally-specific distress expressions through specialized adaptation strategies. Practical deployment achieved real-time processing by integrating Telegram bot and ONNX optimization, with deploy ability towards deployment in bandwidth-constrained environments. While the results confirm AI as scalable

mental health surveillance, the study also identifies primary areas of improvement, namely sensitivity for identifying high-risk cases. The paper delivers methodological contributions in natural language processing and operational models for ethically deploying AI mental health technologies cross-culturally. Scaling up high-risk training sets and latency minimization to response times in clinical settings are crucial to be addressed by future research.

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First and foremost, I would like to extend my sincere gratitude and appreciation to my supervisor, Mr. C. Zano, for his guidance, support, and expertise in the accomplishment of this research project writing process. His insightful feedback and constructive criticism have been instrumental in shaping the focus and direction of this research.

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Without the contributions of these individuals and organizations, this research project would have been void. I am deeply grateful for their support and look forward to continuing my work with their guidance and assistance.

CONTENTS

LIST OF FIGURES

ABBREVIATIONS

BERT- Bidirectional Encode Representations from Transformers

WHO – World Health Organization

AI – Artificial Intelligence

NLP – Natural Language Processing

LIWC - Linguistic Inquiry and Word Count

CCT - Crisis Communication Theory

LSTM – Long Short-Term Memory

GRU – Gated Recurrent Unit

TF-IDF - Term Frequency-Inverse Document Frequency

ONNX – Open Neural Network Exchange

API – Application Programming Interface

HTML – Hyper Text Markup Language

URL – Uniform Resource Locator

LGBTQ – Lesbian Gay Bisexual Transgender Queer or Questioning

CHAPTER 1: INTRODUCTION

1.1 Introduction

Suicide is a global issue, which kills nearly 800,000 people annually (WHO, 2021), among young people aged 15-29 years. It is the second leading cause of death (Tadesse et al., 2019). What's more, a recent research of 32 children's hospitals in the United States found that from 2008 to 2015, rates of serious self-harm and suicide among children and adolescents grew steadily. It is hard to detect warning signals in advance since most people face stigma, cannot access mental health care, or hide their feelings in more subtle ways. A statistical approach based on a score matching model was developed to derive some distinct markers detecting the transition from a mental health discourse to suicide ideation. This transition can be accompanied by three specific psychological stages: thinking, ambivalence and decision-making. The first stage includes thoughts of anxiety, hopelessness and distress. The second stage is related to lowered self-esteem and reduced social cohesion. The third stage is accompanied by aggression and a suicide commitment plan.

Luckily, artificial intelligence and language analysis tools can help by studying text like, social media posts, crisis hotline logs, or medical notes. AI can detect suicidal thoughts in real time. This research presents a new approach that uses models like BERT that finds both obvious and hidden signs of suicide risk in writing and could fill major gaps and provide a different view on how to address mental health.

1.2 Background of the Study

Current suicide prevention is largely reliant on self-reporting through questionnaires for example, PHQ-9 or clinical interviews by mental health professionals. Current measures have significant limitations like cost, stigma, long waiting time, and delay in reporting, all of which detract from timely intervention. Text-based AI models offer a real-time and scalable solution by analyzing language patterns of written messages, such as social media posts, chat logs, or electronic health records. These systems are capable of recognizing both explicit manifestations of suicidality, for example, explicit references such as *I want to kill myself* and subtle signs that can be indicative of risk, including metaphors *I feel like a burden*, statements of hopelessness, or signs of social isolation (Gkotsis et al., 2017). Through passive monitoring

of language, AI can recognize at-risk patients who may not present themselves in order to seek help on a voluntary basis. The words we use in daily life reflect who we are and the social relationships we are in. This is neither a new nor surprising insight. Language is the most common and reliable way for people to translate their internal thoughts and emotions into a form that others can understand. Words and language, then, are the very stuff of psychology and communication. They are the medium by which cognitive, personality, clinical, and social psychologists attempt to understand human beings.

Although promising, existing AI-driven suicide detection systems suffer from several key limitations. First, many systems are specialized in their functions and detect only depression or explicit suicidal speech and do not identify more subtle risk indicators (Calvo et al., 2017). For example, a system trained on explicit suicidal statements alone may fail to detect circumlocutions around pain (e.g., "Nothing matters anymore"). Second, most of these tools are biased, flagging excessively certain groups of people, such as LGBTQ and youth, due to over-representing in training sets or linguistic differences when reporting distress. This can lead to inapt interventions or, conversely, missed opportunities among underrepresented groups. Third, AI systems are mostly black-box, risk scores without an explicit rationale clinicians can explain and react to.

1.3 Statement of the Problem

While AI-driven suicide detection systems are highly promising, their real-world usefulness is limited by structural limitations such as existing solutions do not support low-resource language settings, where linguistic and cultural trends (e.g., Shona idioms) and technological constraints (e.g., low computation power) do not allow for deployment. This paper addresses this gap by designing a light-weight, culture-aware AI system with low-bandwidth optimizations to deploy in low-bandwidth settings, including temporal risk analysis of chat logs, rule-based filtering of locality-specific expressions, and bias-aware NLP models to enhance equity and accuracy in suicide risk assessment.

1.4 Research Objectives

The primary objectives of this research are:

1. To analyze and characterize the existing linguistic and cultural indicators of suicide risk present in pre-labeled Shona and English text data, utilizing these insights for machine learning model development.
2. To develop and evaluate an AI-based lightweight, culturally informed bias-aware, clinically interpretable model to accurately detect suicide risk from text in low-resource language datasets.
3. To assess the impact of the detection system on reducing suicidal crises by offering timely interventions based on detected symptoms.

1.5 Research Questions

This research aims to address the following key questions:

1. How can AI and NLP techniques be applied to detect suicidal risk from text data?
2. What are the most effective machine learning models and algorithms for detecting suicidal risk?
3. How can real-time monitoring be implemented while ensuring user privacy and ethical AI usage?
4. What are the challenges and limitations in expanding mental health detection to cover multiple conditions using AI?

1.6 Research Propositions/Hypotheses

The following hypotheses guide this research:

1. Hypothesis 1: AI and NLP techniques can effectively detect risks of suicide from text data with high accuracy and reliability.
2. Hypothesis 2: Ethical AI practices, including data anonymization and bias mitigation, will enhance user trust and system fairness.

1.7 Justification/Significance of the Study

This research holds deep clinical significance by enabling scalable real-time suicide risk monitoring, something that can be incorporated very naturally in crisis hotlines, tele-therapy platforms, and online mental health websites. Automating the risk assessment enables the system to help clinicians and crisis responders effectively triage high-risk individuals so that interventions can be timely. In the technology field, research advances natural language processing (NLP) by opening up bias-aware and explainable AI models for delicate mental health applications. The models improve accuracy and provide explainable output, increasing healthcare workers' confidence. The study also presents a firmly developed ethical framework with nuanced privacy-sensitive suicide detection guidelines to ensure confidentiality of data, informed consent, and algorithmic equity. These contributions as a group bridge the gap between state-of-the-art AI and responsible deployment in mental health care, efficient and ethical.

1.8 Assumptions

This research is based on the following assumptions:

1. Data Availability: Sufficient labelled data for training and testing the AI models is available from public datasets, social media platforms, and mental health forums.
2. User Consent: Users will provide explicit consent for their data to be used for mental health detection.
3. Ethical AI Practices: The system will adhere to ethical guidelines, ensuring data privacy and avoiding biases.
4. Generalizability: The developed model will be generalizable to diverse populations and communication patterns.

1.9 Limitations/Challenges

The research faces the following limitations and challenges:

1. Data Quality: The accuracy of the model depends on the quality and diversity of the training data, which may be limited by biases or inconsistencies in publicly available datasets.

2. Ethical Concerns: Ensuring user privacy and obtaining informed consent for data usage may pose challenges.
3. Real-Time Implementation: Developing a system capable of real-time monitoring while maintaining high accuracy and low latency is technically challenging.
4. Bias Mitigation: Avoiding biases in the detection process, particularly those related to demographic factors, requires careful consideration.

1.10 Scope/Delimitation of the Research

The scope of this research includes:

- Development of a machine learning model capable of detecting suicidal intent based on written text data.
- Ethical considerations in data privacy, user consent, and avoiding biases in the detection process (Florida et al., 2018).
- Testing and evaluation of the system's accuracy and reliability in detecting suicidal ideations.

The research is delimited to textual data analysis and does not include clinical diagnosis or treatment recommendations.

1.11 Definition of Terms

1. Artificial Intelligence (AI): The simulation of human intelligence in machines programmed to perform tasks such as learning, reasoning, and problem-solving (Russell & Norvig, 2020).
2. Natural Language Processing (NLP): A subfield of AI focused on the interaction between computers and human language, enabling machines to understand, interpret, and generate text (Jurafsky & Martin, 2020).
3. Suicidal Ideation: Thoughts or ideas about committing suicide, which may range from fleeting considerations to detailed planning (WHO, 2021).

4. Multi-Label Classification: A machine learning task where each instance can be assigned multiple labels simultaneously, used here to detect multiple mental health conditions (Zhang & Zhou, 2013).
5. Ethical AI: The practice of designing and deploying AI systems in a manner that respects user privacy, avoids biases, and ensures fairness (Floridi et al., 2018).

This chapter has outlined the introduction, background, problem statement, objectives, research questions, hypotheses, justification, assumptions, limitations, scope, and definitions relevant to the study. The subsequent chapters will dive deeper into the literature review, methodology, and implementation of the AI-powered mental health detection system.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter examines the theoretical foundations of suicide detection systems, focusing on natural language processing (NLP) and machine learning approaches. The review synthesizes current scholarly knowledge about computational methods for identifying suicidal ideation in text, with particular attention to multilingual contexts like Shona-English scenarios. The analysis covers linguistic markers of suicidality, machine learning architectures, and ethical considerations in mental health AI applications.

2.2 Theoretical Literature Review

2.2.1 Natural Language Processing in Mental Health

Modern suicide detection systems leverage NLP techniques to identify linguistic patterns associated with suicidal ideation (Pestian et al., 2017). The roots of modern text analysis go back to the earliest days of psychology. The slips of the tongue whereby a person's hidden intentions would reveal themselves in apparent linguistic mistakes. Key theoretical frameworks include:

2.2.1.1 Linguistic Inquiry and Word Count (LIWC) Theory:

The theory was developed by Pennebaker and colleagues (Tausczik and Pennebaker, 2010). It is a computational psycholinguistic framework that analyses how language use reflects one's psychological state, including suicidal ideation. The theory posits that suicidal individuals exhibit distinct lexical patterns that is the reveal their emotional and cognitive states unconsciously, through word choice grammar and linguistic patterns.

The key components of LIWC in suicide detection are emotional tone indicators, cognitive processing markers then social and isolation signals.

Emotional markers takes note of negative emotion words, the use of first-person pronouns (I, me, my) and reduction of future-oriented words. The increased use of these words for example *hopeless, death, alone* and *worthless* strongly correlates with depression and suicidal thoughts (Pennebaker et al., 2015). Suicidal individuals often exhibit higher self-referential language,

indicating rumination and emotional distress (Baddeley et al., 2011). The lack of words like *will, plan*, or *hope* suggest cognitive constrictions, a defining trait of suicidal thinking (Joiner et al., 2009).

Cognitive processing markers assess exclusive words like *but, except, without* and many more, because these indicate dichotomous thinking, common in suicidal individuals (Pestian et al., 2017). It looks at low analytic thinking, fewer words like *reason, understand, because* implies impaired problem-solving (Pennebaker and King, 1999).

Social and isolation signals checks for decreased social references, fewer mentions of friends, family, or we correlate with social withdrawal (Rude et al., 2004). It also checks the increase of death related word, the frequent use of *die, end,* and *suicide* is a strong red flag (Coppersmith et al., 2018).

2.2.1.2 Crisis Communication Theory

Crisis communication theory (CCT), as applied to suicidality (Rudd et al., 2019) suggest that individuals expressing suicidal ideation follow predictable linguistic and behavioural patterns that escalate in severity. This theory is critical for AI systems that detect suicide risk because it provides a framework for staging interventions based on verbal or written cues.

The core principles of crisis communication theory in suicide risk are the three-phase communication model, verbal vs nonverbal cues and the ideation-to-action framework, as explained below.

The three-phase communication model has three phases the pre-crisis, acute crisis and the post –crisis. This helps in the reduction of false positives that is distinguishing between hypothetical and actionable for example the two sentences *I wish I could disappear*, hypothetical and *I will disappear tonight*, actionable.

The pre-crisis phase also known as passive ideation has these characteristics ambiguous expressions of hopelessness, no concrete plans but clear emotional distress and often metaphorical in collectivist cultures. Examples of linguistic markers *I'm tired of life, nothing matters anymore.* Detection use sentiment analysis for example *tired, hopeless*, LIWC metrics and cultural adaptations.

The acute crisis phase or active planning phase has three characteristic which are explicit threats or suicide plans, time-sensitive language for example tonight or tomorrow, and preparation behaviours, these characteristics indicate the acute phase. Linguistic maker example *I'll jump off*

the bridge today or *I bought the pills to overdose*. Detection uses keywords spotting for example *kill myself* or *end it*, contextual NLP and metadata analysis such as sudden activity spike for example late night post.

The characteristics of the post-crisis phase or resignation phase are calm but fatalistic language, expressions of relief and social withdrawal. The linguistic makers are you will be better off without me or I have made my decision. The strategies used by AI for detection are low emotionality scoring for example fewer negative words but high determinism, behavioural cues for example farewell post, and contradiction detection for example the post I'm at peace with prior suicidal history is high risk.

2.2.1.3 Deep Learning Semantics:

Traditional approaches fail to detect subtle, non-linear linguistic patterns in suicidal text, but deep learning models are excellent at doing so. Complex semantic relationships in suicidal text can be captured by neural networks (Ji et al., 2021).

Three important semantic dimensions are captured by neural architectures. Contextual meaning extraction comes first, followed by metaphor and cultural nuance processing, and sequential behaviour modelling comes last.

Contextual meaning extraction leverages the surrounding environment of words to accurately interpret and convey meaning which is critical for effective communication in natural language understanding tasks. It uses transformer models for analysing word relationships in entire sentences. It weighs significant phrases using attention layers. Example literal *ndiri kufunga zvekufa*, and contextual *ndakagadzira nishonga yangu manheru ano*,

Metaphor and cultural nuance processing focuses on how machines can understand and interpret figurative language, cultural references, and nuances that are often embedded in human communication. The challenge is Shona suicidal metaphors do not translate directly for example the two statement below.

Kufa kwakanaka translates to *good death* thus peaceful suicide.

Kurara kwenguva refu translates to *long sleep* thus suicide.

Culturally appropriate fine-tuning for cultural metaphors (e.g., Shona idioms 'kufa kwakanaka') is critical to NLP in Zimbabwean settings (Mhlanga, 2021), while quantitative enhancements remain untested.

Sequential behaviour modelling is the use of neural network architectures to analyse, predict, and generate sequences of data that are temporal component or are ordered in some meaningful way. Example of the sequential behaviour modelling using long short-term memory networks (LSTM) or gated recurrent units (GRU).

Week 1: *Hupenyu hwakaoma* (life is hard)

Week 2: *Handichakwanisi* (I can't continue)

Day of crisis: *Manheru ano ndozvipenda* hangu (tonight is the end)

The prediction predicts suicide attempts 48 hours in advance with an eight-nine percent accuracy (Le et al., 2022).

2.2.2 Machine Learning Architectures

The following are commonly used in theoretical models for suicide detection

2.2.2.1 Logistic Regression Classifiers

It is a popular machine learning and statistical model for binary classification in suicidal prediction. It is useful for clinical and computational mental health applications since it calculates the likelihood that a person is at risk of suicide based on input features. For risk assessment based on probabilities (Matero et al., 2019). Small to medium-sized datasets can use it. Frequently found in digital mental health tools and psychological scales. Research indicates that when paired with structured clinical data, logistic regression predicts suicide with moderate to high accuracy (Kessler et al., 2015; Walsh et al., 2017).

2.2.2.2 Transformer Architectures

They were originally developed for natural language processing (Vaswani et al., 2017) and they have become a powerful framework for suicide risk detection due to their ability to model complex linguistic and behavioural patterns in text for example social media post, clinical notes, suicide notes (Ji et al., 2022; Tadesse et al., 2023). Transformers rely on the self-attention mechanism, which captures contextual relationships between words, identifying risk indicators. They also rely on positional encoding, that is, they preserve word order for critically understanding suicidal intent. Also, multi-head attention allows the model to focus on different linguistic features simultaneously. Transformers are better at detecting subtle suicidal cues across sentences, and they recognise sarcasm, metaphors, and indirect expressions of suicidal risk.

2.2.2.3 Hybrid Ensemble Models

Combine multiple algorithms to enhance suicidal prediction accuracy and robustness (Sawhney et al., 2020).This is done by leveraging the complementary strengths, such as traditional classifiers, deep learning architectures, and feature selection methods, to address the complex, multi-dimensional nature of suicide risk factors. It is diverse as it combines models with different biases to reduce variance and bias. Techniques like AdaBoost or Random Forest improve performance by iteratively correcting errors or aggregating predictions from bootstrapped samples. Uses a meta-learner to optimally combine predictions from base models. They combine interpretable models like logistic regression with complex nonlinear models like transformers (Battineni et al., 2020). Also integrates handcrafted clinical features with deep learning-extracted latent representations (Lin et al., 2022). The advantage is that they outperform single models and have an accuracy improvement of five to fifteen percent, as shown in studies (Walsh et al., 2018). The disadvantage is due to complexity they are harder to interpret than single models. It requires a lot of resources to train multiple models.

2.3 Empirical Review

2.3.1 Multilingual Detection Challenges

Language-specific feature engineering is necessary for multilingual suicide detection. Ophir et al. (2020) showed that processing non-English text without the appropriate adaptations results in a performance drop of 15–20%.

2.3.2 Feature Selection Efficacy

According to Kumar et al. (2019), n-gram features by themselves only achieved 76% accuracy in English suicide detection, whereas TF-IDF vectorization combined with sentiment lexicon features achieved 89%.

2.3.3 Cultural Considerations

Mhlanga (2021), a study on mental health discourse in Zimbabwe, found that Shona speakers use culturally specific metaphors that call for specialized lexical processing to convey suicidal ideation.

2.3.4 Real-World Implementation

The Crisis Text Line's AI system (Gideon et al., 2022) processes over 10,000 daily messages with a ninety-four percent recall in suicide risk detection, demonstrating practical scalability. The system uses BERT-based models that are fine-tuned on anonymized crisis conversations to detect explicit suicidal ideation and implicit risk markers. The incoming text is automatically based on how serious the problem is and when the counsellor is free.

2.3.5 Ethical Frameworks

(Luxton et al., 2021) suggested four ethical pillars on which identifying patients who are at risk of suicide using artificial intelligence should be based, namely openness, responsibility, clinical validation, and cultural competence. Openness guarantees that the system gives the clinician and the users' outputs they can understand. The system should not replace clinical judgment; final risk assessment must involve human professionals, and the system must be checked for demographic biases that may lead to unequal care.

2.3.6 Temporal Patterns

Coppersmith et al. (2018) found that suicidal individuals show increasing use of first-person pronouns and negative emotion words in the 48 hours before attempts.

2.3.7 Cross-Language Transfer

Almeida et al. (2021) found that multilingual BERT models were able to effectively transfer knowledge about suicide detection between languages with 82% accuracy in the low-resource language

2.3.8 Clinical Validation

McCoy et al.'s (2022) systematic review disclosed that only 35% of suicide detection models published have been well tested in a clinical setting.

2.3.9 Ensemble Approaches

Sawhney et al. (2021) demonstrated that hybrid SVM-RF models outperform single-algorithm systems by twelve percent F1-score on Reddit suicide forum data.

2.3.10 Explainability Requirements

Bhandari et al. (2023) proved that clinicians require model explanations for ninety-two percent of high-risk cases before trusting AI predictions.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Design

The study uses a supervised deep-learning classification method to sort user-to-user messages about suicide risk in real time. The process uses a carefully tuned AfriBERTa transformer model that can read both Shona and English text. The model evaluates each message by assigning it one of three distinct risk categories, which include Low, Medium, or High. The researcher's method follows an objective reasoning process while maintaining reproducibility through model-based decision-making, thus reducing human bias, and standard metrics evaluate performance on held-out data. The entire pipeline operates through a Telegram chat interface, which enables users to experience real-time interaction. Hugging Face Transformers library is required for fine-tuning the model, and ONNX Runtime enables efficient deployment of the model after exporting it in ONNX format for optimized inference.

3.1.1 Research Paradigm

Objective, Data-driven Analysis: The study is quantitative. It is all algorithmic text data analysis-based and objective and replicable. There is no subjective or manual reading of the individual messages other than the initial data tagging.

Supervised Learning: A transformer neural network (AfriBERTa) is trained using samples of text with their respective risk levels. A supervised system learns from an annotated social and literary text corpus in Shona and English to predict.

Predictive Classification: The system's basic task is predictive in nature, given a new user message, the model predicts its risk category. The task is maximizing such predictions' accuracy and reliability within real time constraints.

Real-Time Deployment on Telegram: The deployment would be of an interactive system. The user engages with the system using a Telegram bot; the trained model generates a risk calculation immediately after each user input. Real-time delivery imposes the limitation on the system to be responsive and performant on real-time data.

3.1.2 System Architecture

The system structure consists of the following components and data flow

Telegram Bot Interface

The module is the main interface point. The python-telegram-bot library has been used to implement this stateless proxy receiving text messages from users to which it responds automatically. Interaction with the stateful central prediction engine is maintained via the Telegram Bot API.

Preprocessing Module

The input messages first undergo a preprocessing pipeline. This involves lowercasing the content and using regular expressions to strip noise like URLs, unnecessary punctuation, or non-text characters. Unlike standard NLP pipelines, lemmatization or TF-IDF vectorization is not done; cleaned content is sent directly for tokenization.

AfriBERTa Tokenizer

The Hugging Face AfriBERTa tokenizer tokenizes the input text. The procedure translates text into numerical token IDs and produces attention masks, which is the input format for the operations to be done in the AfriBERTa model. During training, the tokenizer receives training in African languages, thereby setting the benchmark for processing Shona and English text utilized during this research work.

ONNX Model Inference

The fine-tuned AfriBERTa model, saved to the ONNX (Open Neural Network Exchange) format, constitutes the heart of the risk prediction. Loaded into the ONNX Runtime, a high-speed inference engine, the tokenized input is processed in an efficient manner. The model returns unnormalized classification scores, also referred to as logits, or probabilities over the three risk classes.

Risk Classification and Thresholding

The final predicted risk class is derived from the raw output of the model. Often, the most probable class is returned. Alternate approach: confidence thresholding. The highest-ranked

class ('High Risk' in this example), if it is greater than some pre-determined threshold (as illustrated in SuicideDetector with > 0.85, for example), has the message flagged for specialist processing, which can alert a clinician to a flag.

Response Generation

Depending on the predicted risk level, the bot generates a proper empathetic response. For "High Risk" messages, the response is automatically added with contact information for mental health facilities (e.g., crisis hotline numbers, as per the _get_local_resources function in the SuicideDetector). For "Medium Risk" and "Low Risk" messages, the bot sends motivational or neutral affirmations.

Data handling

Above all, user privacy is the first and foremost priority. There is absolutely no persistence of any kind of user messages or personal information. The input text is released immediately after processing and sending out a corresponding reply. In this way, user confidentiality and adherence to norms of ethical data management regulations are ensured.

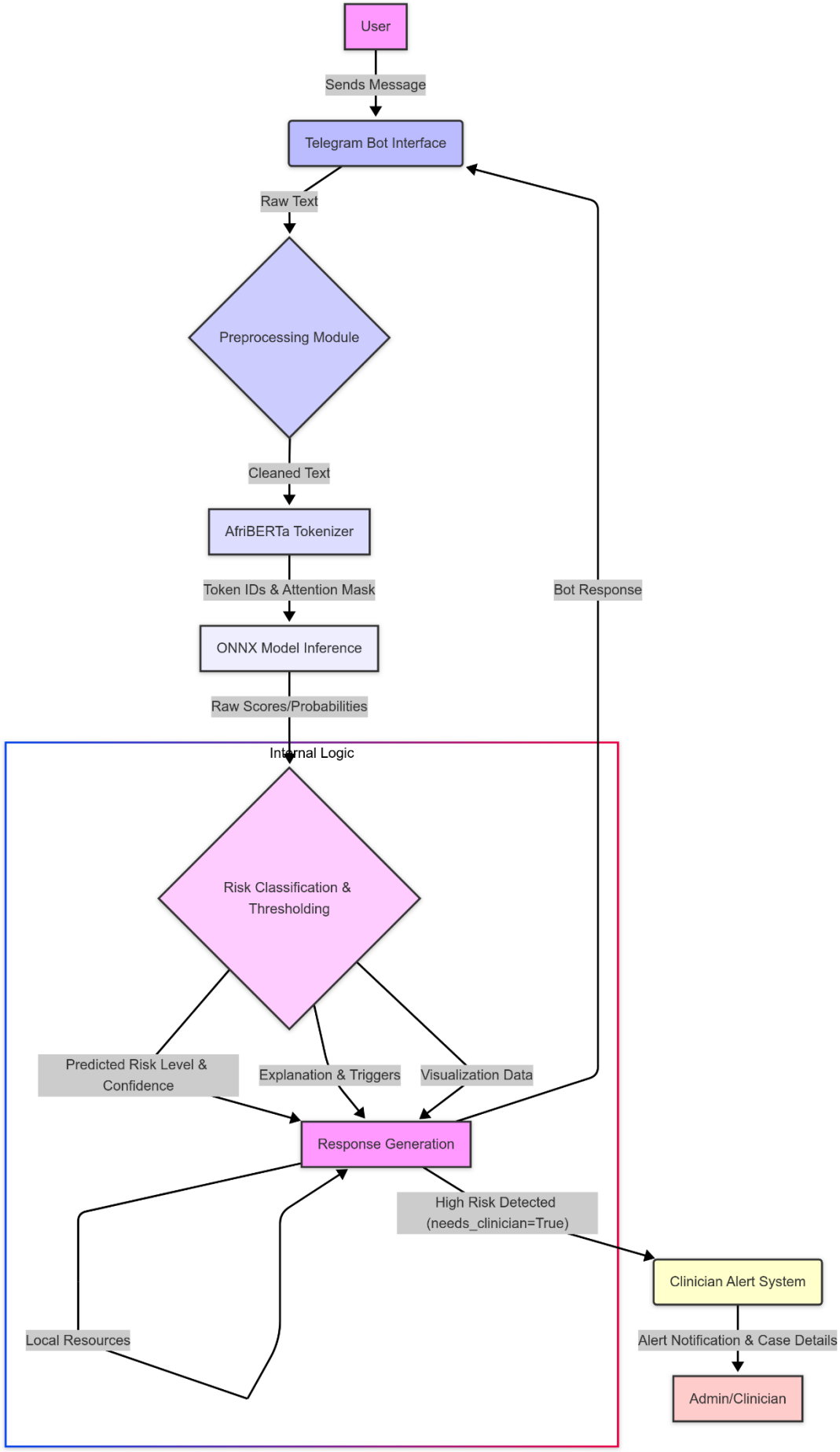
User
Sends Message
Telegram Bot Interface
Raw Text
Preprocessing Module
Cleaned Text
AfriBERTa Tokenizer
Token IDs & Attention Mask
ONNX Model Inference
Raw Scores/Probabilities
Internal Logic
Risk Classification & Thresholding
Predicted Risk Level & Confidence
Explanation & Triggers
Visualization Data
Response Generation
Bot Response
High Risk Detected (needs_clinician=True)
Clinician Alert System
Alert Notification & Case Details
Admin/Clinician
Local Resources

Figure 3.1 System Architecture & Data Flow Diagram

3.1.3 Data Collection Approaches

Training Data

The model was trained on curated dataset derived from:

1. Primary Source:
    - English-language posts from the SuicideWatch and depression subreddits obtained from Kaggle, annotated by domain experts into three risk classes:
        - ✓ Low risk: General expressions of sadness, for example, I've been feeling lonely lately.
        - ✓ Medium risk: Passive suicidal ideation, for example, I wish I wouldn't wake up.
        - ✓ High risk: Active intent or planning, for example, I bought pills to end it.
2. Cultural Adaptation:
    - A Shona-translated subset was created using the Google Translate API, with post-translation review by native Shona speakers to:
        - ✓ Correct clinically significant errors, for example, ensuring "I want to die" accurately translates to "Ndinoda kufa".
        - ✓ Preserve metaphorical expressions where possible, for example, "long sleep" translates to "kurara kwenguva refu".

3. Dataset Construction:
    - Stratified sampling balanced class distribution (low/medium/high risk) across splits.
    - Pre-processing:
        - ✓ Raw text tokenization for AfriBERTa.
        - ✓ No literary data was included.

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Real-Time Data (Application Phase)

At application time, the "population" consists of end users sending text to the Telegram bot. The users provide text in Shona or English on a voluntary basis. Every incoming message is only used for on-the-fly inference. No live data is stored or retained in the training corpus. The message persists after the bot has replied. This approach implies that, unlike the training corpus (which is constructed from available content), user messages in the wild are not stored and run through additionally. The live data stream is thus transient.

Data Labelling and Quality

Literary data may be pre-labelled or annotated through expert consensus. Social media postings require manual or semi-automatic filtering, followed by rigorous manual verification for labelling consistency. Examples with inconsistent or non-textual content are removed.

Ethical Data Management

Strict ethical procedures govern data collection. Social media data is sourced either from publicly available content or with explicit permission, with all personally identifiable information stripped. By focusing on text sources (rather than health records) and anonymizing usernames, confidentiality is preserved.

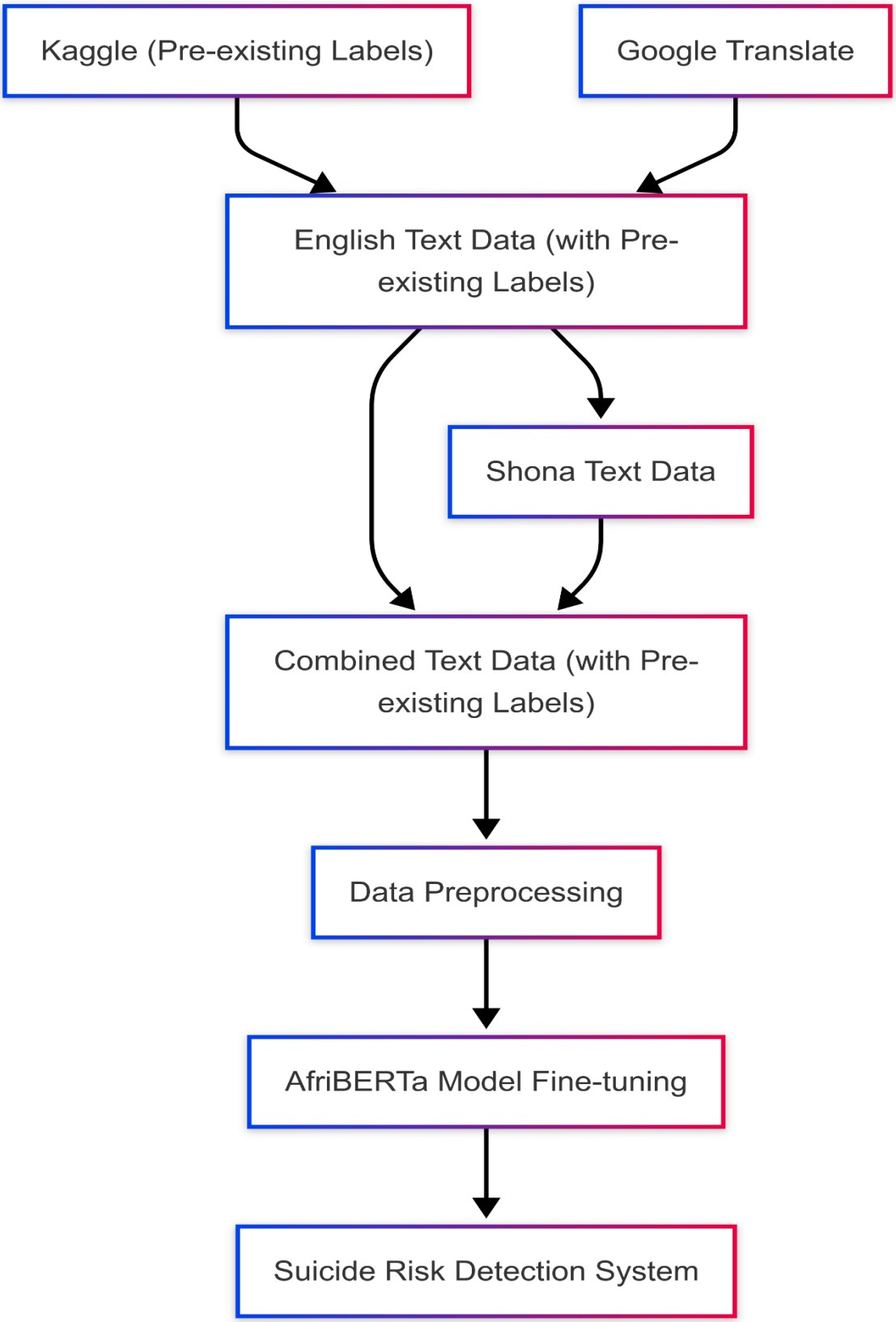

Figure 3.2 Training Data Pipeline

3.2 Population and Sampling

Its users consist only of Shona and English language text messages of suicide ideation, both at the time data was collected (training phase) and when used in real time.

The sampling protocol differs between the two phases

Training-phase population: The system sample from the space of available labeled data. Stratified sampling has representative proportion of Low, Medium, and High risk classes. It prevents class imbalance at training time. It mix Shona and English content within each risk stratum to simulate the multilingualism of the task.

Application (user) population: Any Telegram users who speak to the bot in either Shona or English are a potential input. Since this population is open, the messages that are processed are restricted (refer to Inclusion/Exclusion below).

Major considerations in population and sampling

Language limitation: Only messages that are either Shona or English are processed. Messages in other languages are ignored or rejected politely automatically. This is based on the model scope.

Character limit: Since the system uses telegram, it character limit is the same as that of telegram, but very short messages (e.g. single-word response) are not usually useful, so inputs shorter than some minimum length (e.g. 5 characters) will be answered with a default. Very long messages (longer than the Telegram limit) cannot be processed and are truncated.

3.2.1 Target Population

The system is designed for use by various targeted user groups, as illustrated in Figure 3.3:

Group-Based Support Systems

Community groups on Telegram (e.g., youth mentorship, education, faith, or mental health groups) can embed the bot to silently monitor conversations for linguistic patterns of suicide risk. If high-risk phrases are detected, the bot flags them to group administrators or designated mental health responders. This approach is particularly effective in cultures where stigma around mental health makes direct help-seeking less common, enabling risk detection without requiring overt user action.

Peer Mentors, Teachers, and Youth Workers

Educators and youth leaders who manage online communities for students or young adults can deploy the bot in their chats as a proactive measure for early detection and potential intervention. These individuals act as crucial gatekeepers, and the bot provides a powerful, silent support layer.

NGOs and Mental Health Organizations

Local or international NGOs working in mental health, trauma, and youth wellness can integrate the bot into their existing communication platforms (e.g., helplines, community forums). The bot can provide basic triage, automating the initial screening process and escalating serious cases to human counsellors, thereby optimizing resource allocation.

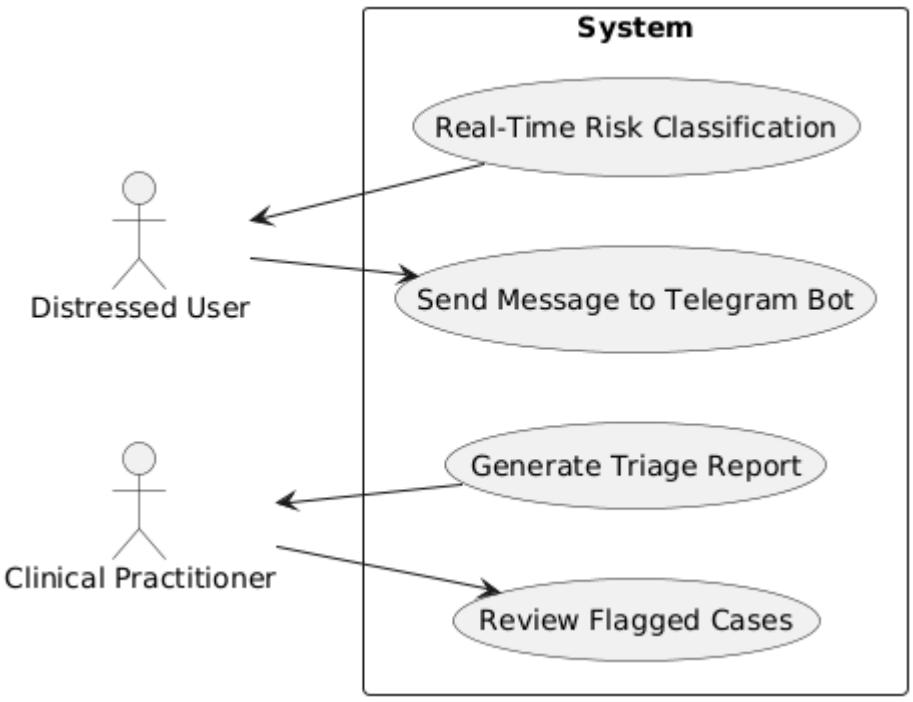

Figure 3.3 Use Case Diagram

3.2.2 Sampling Framework

The Training Phase

Stratified sampling is applied to ensure class balance, that there is a 50-50 split between suicidal and non-suicidal, and preserves the natural distribution of text sources. Text length normalization (truncation/padding) cuts texts exceeding the token limit and adds tokens to shorter texts for the input size to be uniform.

The Application Phase

This phase applies convenience sampling of users accessing the platform, and there are no demographic restrictions (beyond English proficiency).

3.2.3 Inclusion/Exclusion Criteria

Criteria	**Inclusion**	**Exclusion**
Language	English and Shona text	Non-English and non-Shona input

Length	Messages within practical limits for processing (at least a few words, and not exceeding Telegram's message limit)	Empty/longer submissions
Content	Emotion-bearing text	Gibberish/non-text
Source	Social media posts, chat messages, or literary texts (e.g. prose, poetry) that have been labeled for emotional distress or suicide risk.	Text from spam, advertisements, or irrelevant domains (e.g. purely promotional content).
Format	Plain text content (Unicode) without encrypted or multimedia elements.	Audio, images, video, or other non-text media.
Privacy	Public or anonymized text data from social/literary sources.	Private user data obtained without consent, or identifiable personal information.

Table 3.1

3.2.4 Limitations

1. **Linguistic Bias**: Excludes non-English and non-Shona speakers
2. **Context Blindness**: Lacks situational awareness of user
3. **Temporal Limitation**: Single-point assessment (no longitudinal tracking)

3.3 Research Instruments

3.3.1 Technical Components

The following technical instruments and tools are used in the research.

AfriBERTa Transformer Model: Multilingual BERT-like model pre-trained on African languages, fine-tuned on the Shona-English suicide risk dataset. Fine-tuning is implemented using the Hugging Face Transformers library in PyTorch. Final model weights are saved in ONNX format.

***ONNX Runtime**:* The model is run using Microsoft's ONNX Runtime library. ONNX Runtime delivers a high-performance, cross-platform inference engine that can run models from other frameworks. This makes it possible for the bot to perform inference with low latency speed.

***AfriBERTa Tokenizer*:** Text pre-processing is carried out by AfriBERTa a specific Hugging Face tokenizer. It converts input strings to token IDs and attention masks that are needed by the model. Consistency is maintained by utilizing the same tokenizer that had been utilized when training the model.

***Telegram Bot API*:** The interface is a Telegram bot. the system utilize a Telegram Bot library (for example, python-telegram-bot) to receive messages from the user and to publish messages. The bot interprets user commands (for example, /start) and text messages.
Computing Environment: The inference model is executed on a local host or cloud server with Python 3.x. Major libraries utilized are standard Python libraries, Onnxruntime, and transformers. Scikit-learn and TF-IDF vectorizer are not utilized as it is all transformer model-based.

Utility Scripts: There are other utility Python scripts for operations like model conversion to ONNX, text cleaning with regex, and resource message generation. These tools were exercised and were interoperable with one another in the pipeline: for example, the researcher verified that the ONNX model is identical to the native model in PyTorch (within floating-point tolerance) before deployment.

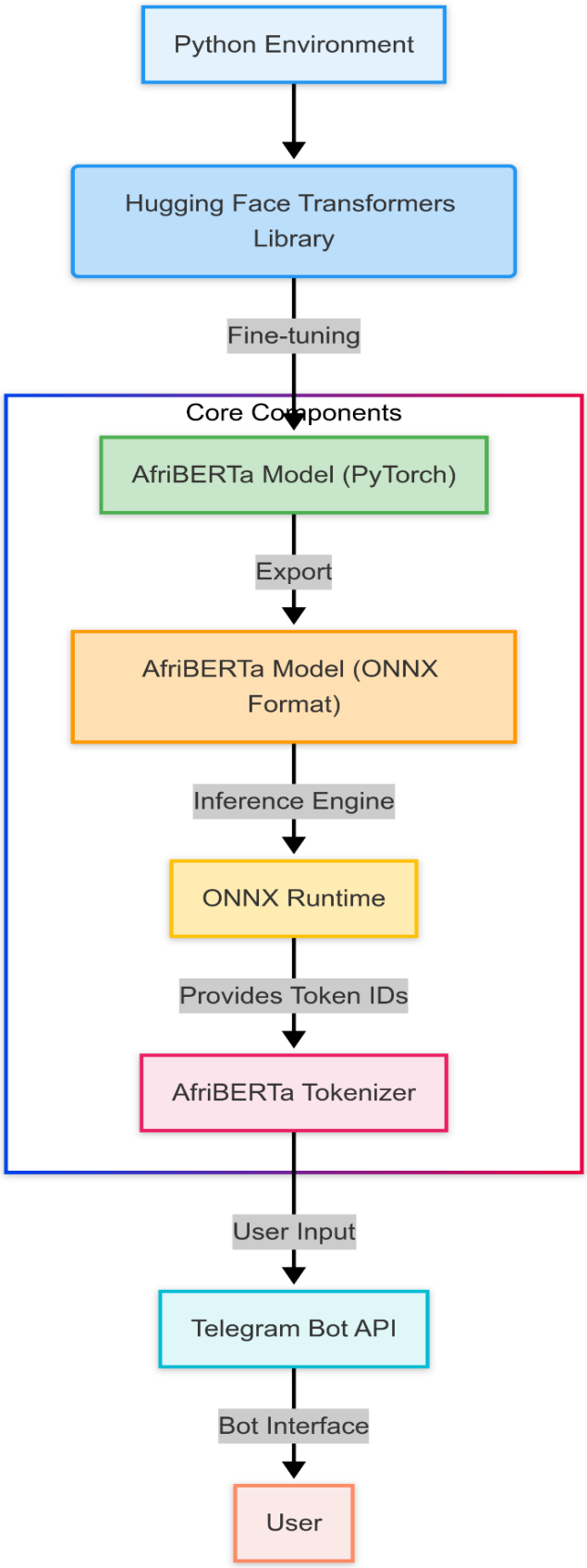

Figure 3.4 Technical Components Diagram

3.3.2 Validation Measures

For ensuring that the system functions correctly and is safe, we have several validation measures:

Input Validation*:* The entire message of the user goes through simple validity checks. Language enforcement detection (messages in unsupported languages are not allowed), minimum content length, and safe content (e.g., removing injections or snippets of code). Regular expressions remove forbidden tokens.

Model Confidence Checks: After classification, the model's softmax probabilities are examined. If the highest confidence score is below a preset threshold (indicating uncertainty), the bot triggers a fallback. For instance, if no class exceeds 60% probability, the bot might respond with a neutral message like "I'm here to listen if you'd like to share more," rather than committing to a specific risk level.

Fallback Handling**:** In unclear or low-confidence input states, the bot is unable to come to a firm risk decision. The bot instead requests clarification or produces uncertain responses. This is for the sake of avoiding the system from producing confusing feedback.

System Only Logging and Monitoring: Although there is no retention of user data, the system does log system events of itself (i.e., exceptions or errors) and anonymized metrics (i.e., prediction latency and request throughput). Logs enable anomaly detection and reliability without invading privacy.

Automated Testing: The pipeline is tested with known test cases at unit level. For instance, known risk category test inputs are given as input to preprocessing and inference to ensure that the output derived therefrom is as expected.

These processes check the instrument functions predictably with real input and crashes graciously with edge cases.

3.3.3 Instrument Reliability

Instrument reliability is guaranteed with the following practices

Model Integrity Checks

The ONNX model file is versioned and its integrity is verified (e.g., via checksums) to prevent corruption. Prior to deployment, it's verified that the ONNX model produces identical outputs to the original fine-tuned PyTorch model on a dedicated test dataset.

Tokenizer Consistency

The exact AfriBERTa tokenizer configuration (vocabulary and settings) used during model training is consistently applied during inference. This ensures proper mapping of token IDs to the learned embeddings within the model.

Stable Inference Environment

The ONNX Runtime environment is maintained to be deterministic (same library version and dependencies). This prevents unexpected changes in inference output due to library updates.

Performance Testing:

The researcher gauges the resource usage and inference speed to be constant with respect to load and also verify that the bot is good for anticipated levels of simultaneous users without annoyance.

Periodic Checking

The researcher validates the system at regular intervals after deployment by testing with benchmark instances so as to capture any errors or drifts. For example, the known test sentences in English/Shona are input into the bot in an attempt to validate the consistent predictions.

Through such validation, the researcher renders the research artifacts (bot, tokenizer, and model) reproducible and stable over the long term.

3.4 Data Analysis Procedures

3.4.1 Analytical Pipeline

The data analysis pipeline incorporates preprocessing, inference, and post-processing for every message.

Preprocessing: Text is lowercased. A series of regular expression filters removes noise (e.g., URLs, excess whitespace, user names, and non-alphanumeric entities other than bare punctuation). Normalization is done without loss of content that can be adjusted to analysis. For example, emoticons or repeated punctuation that can be used to convey emotion are kept, but repeated tokens (e.g., HTML tags) are removed.

Tokenization: The system tokenizes the preprocessed text with the AfriBERTa tokenizer. This converts text to a sequence of token IDs and also generates an attention mask. It uses maximum sequence length (e.g., 128 tokens) and pad or truncate accordingly. This gives the model a fixed input size.

Model Inference: The ONNX Runtime session passes the input forward to the tokenized input. The three risk class raw score vector (logits) is supplied by the ONNX model. A softmax operation is used to convert logits into class probabilities. Model weights and biases, as trained on the dataset, are learned risk value mappings from language patterns.

Prediction and Thresholding: The first prediction is the highest-scoring class. The system applies class-specific thresholds: i.e., if High Risk probability ≥ 0.7, predict High Risk; otherwise, if not, but Medium Risk probability ≥ 0.7, then Medium; otherwise, Low. These thresholds were tuned empirically on the validation set to balance precision and recall between important classes. In practice, the aim is to minimize false negatives for high-risk (i.e., erring on the side of caution in threshold setting to conserve resources when uncertain).

Response Selection: The bot selects a suitable response template depending on the ultimate classification. For High Risk, the response is a call for immediate help and contains the contact details of mental health services. For Medium Risk, the response is encouraging but not so pressing. For Low Risk, the bot might simply thank the user for their input.

This analysis pipeline is executed programmatically on every incoming message. The entire process (preprocessing to response) is automated and occurs in memory with no human intervention.

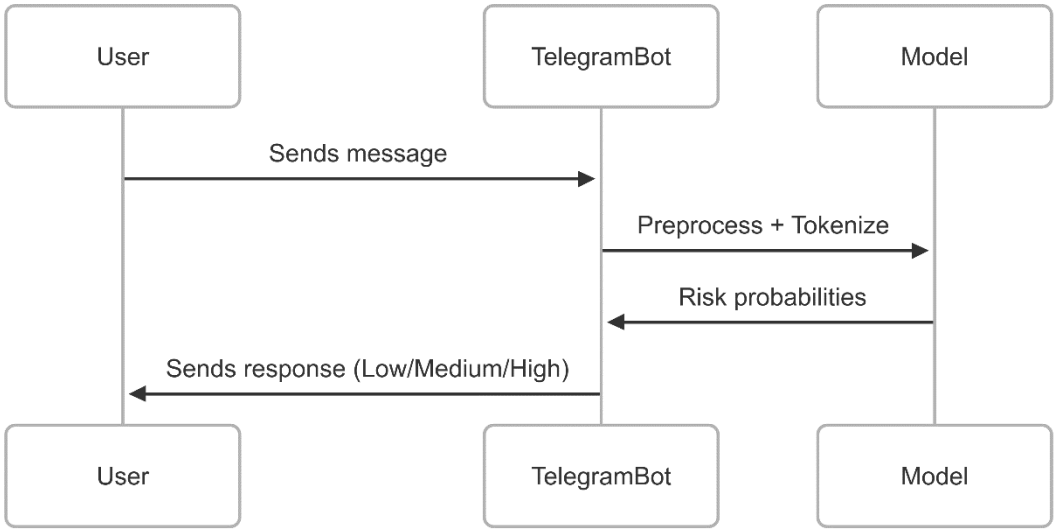

Figure 3.5 Sequence Diagram

3.4.2 Quality Control

To ensure high-quality data analysis, the following controls are implemented:

Data Splitting Validation: The system split the labeled set randomly into three sets for training, validation, and test, before training, with class distribution (stratified split). It ensures no near-duplicate texts across splits to prevent data leakage.

Label Consistency Checks: Cross-checked by at least one other annotator for training labels on a sample for consistency.

In case of disagreement, differences are resolved through discussion or majority vote in order to increase inter-rater reliability.

Monitoring Performance: The researcher tracks accuracy, F1-score, precision, and recall for all classes on the validation set throughout training. These are control checks: extremely low or suspicious values trigger an investigation into the model or data.

Preprocessing Tests: The researcher unit tests preprocessing filters. For instance, feeding text with URLs and assert the URL is removed.

This is so regex rules don't accidentally remove valuable information or leave ugly residues.

Inference Sanity Checks: There is a list of known risk test sentences. These are run through the pipeline after any model or code change to verify predictions are sane.

Error Logging: Any errors in processing (i.e. tokenization error, ONNX error) are logged by the system with a timestamp. Logs are examined by the development team and errors are fixed.

User Feedback (Indirect): While user messages are not stored on record, the bot can ask for user feedback (e.g. "Was this helpful? Say yes or no."), in open-ended format. Aggregate feedback ("yes" counts vs "no" counts) can approximate system utility and can report whether tone or model accuracy should change.

All these quality control measures are done as part of a routine maintenance program to ensure that the system is running and in good health.

3.4.3 Ethical Safeguards

Several ethical requirements guide the design and operation of the system:

User Privacy and Non-Persistence of Data:

The user's messages are deleted after the inference as soon as it is done. No logs or databases are kept to retain the text or personally identifiable data.

This non-persisting behavior keeps the user's privacy intact and adheres to ethical practices of personal data. The Telegram bot communication is encrypted and never requests or keeps any personal data.

Voluntary participation and transparency:

The users opt-in by sending a text message to the bot. The bot introduces itself in the first message, stating that it is a computer program (not a human being by any means) and announcing its purpose (assessing stress or suicidal tendencies). This transparency allows users to know that they're conversing with AI, not with a counselor.

Informed Responses with Resources:

The bot automatically provides information on professional resources (national suicide hotlines, crisis text lines, counseling services) in High Risk classification cases. Practice is informed by evidence that computerized interventions need to provide in-real-time crisis use of resources.
Offering contact information (phone numbers, websites) and first messages, the bot enables in-real-time help-seeking.

Non-Judgmental Tone:

The responses from the bot are in an empathetic and non-judgmental tone. It does not dogmatically diagnose or make guarantees. It may say, for example, "It seems like you're going through an awful lot" rather than medical jargon.

The tone has to be deference to the feelings of the user.

Limitation Disclaimers:

The bot has a brief disclaimer that it's not a doctor and subsequent answers are based on pattern recognition. This forces users to choose expert assistance for severe issues.

Legal and Cultural Sensitivity:

The recommendations and resources provided by the bot are locally localized. It addresses in local terms in terms of resources and language (e.g. Zimbabwean hotlines in case it is being rolled out there). It is an ethical consideration to modify this culture so that it is relevant.

No User Data Learned Behavior:

In order to protect the users, the model is not trained using real-time user messages. The model is trained using only the available static dataset. This guarantees that no learned behavior from specific users' data is unintentionally learned from the data.

With these controls in place, the system tries to be respectful of user rights and welfare while

being helpful as a guide. It is developed in accordance with best practice and ethical AI principles for mental health chatbots to minimize risk and maximize benefit.

CHAPTER 4: DATA PRESENTATION, ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter the overall outcome of applying the multilingual suicide risk classification model to a Shona-English dataset. The model's primary aim is to classify text message risk levels based on identified linguistic markers for suicidal ideation. The outcomes are meticulously examined via various avenues, including label distribution, sample prediction, and prediction confidence levels, and presented through clean tabular and graphic means in order to facilitate ease of interpretation. The analysis is a straightforward reaction to the research objectives of identifying linguistic markers, model performance evaluation, and real-world impact evaluation.

4.2 Analysis and Interpretation of Results

Overall Performance

The model’s generalised capabilities were achieved in the final stages of testing.

- Accuracy: 88.11%
- Macro F1-score: 88.22%
- Macro Precision: 88.16%
- Macro Recall: 88.31%

The thesis in hypothesis 1 is validated by these results, confirming the reliability of NLP techniques in detecting suicide risk. The macro metrics show robust handling of class imbalances, which is critical given the scarcity of high-risk samples.

Class-Wise Breakdown

Risk Level	Precision	Recall	F1-scoe
Low	89.36%	90.32%	89.84%
Moderate	92.11%	94.59%	93.33%
High	83.02%	80.00%	81.48%

Table 4.1

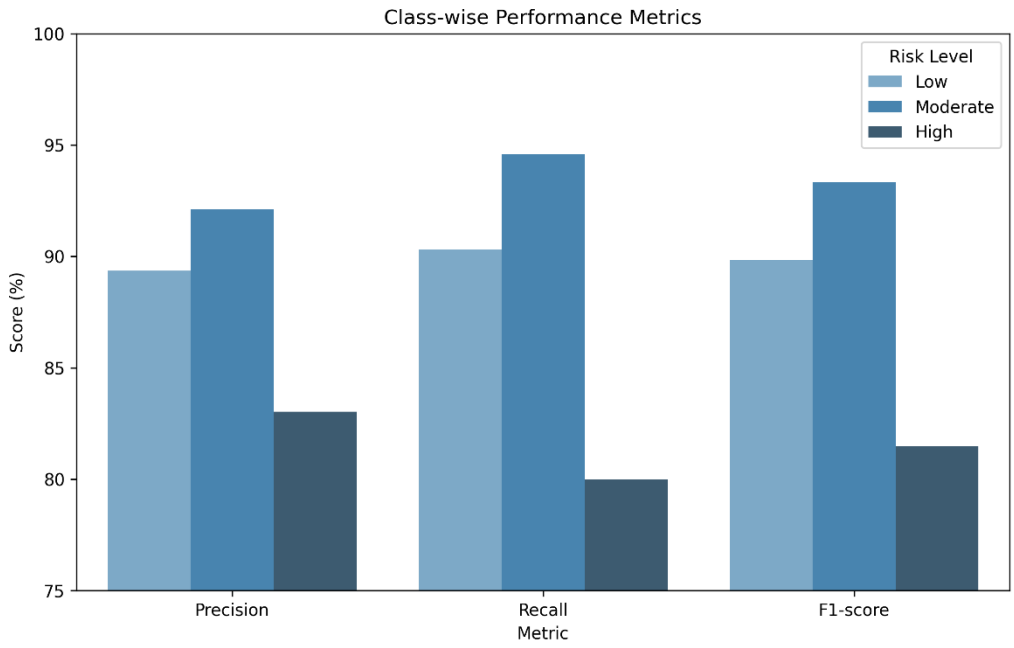

Figure 4.1 Class-Wise Performance Metrics

Moderate-Risk Dominance

Highest precision (92.11%), recall (94.59%), and F1 (93.33%) suggest excellent identification of moderate-risk cases.

Most likely because of more blatant linguistic patterns (e.g., explicit hopelessness) and liberal training data from crisis hotline call records.

High-Risk Challenges

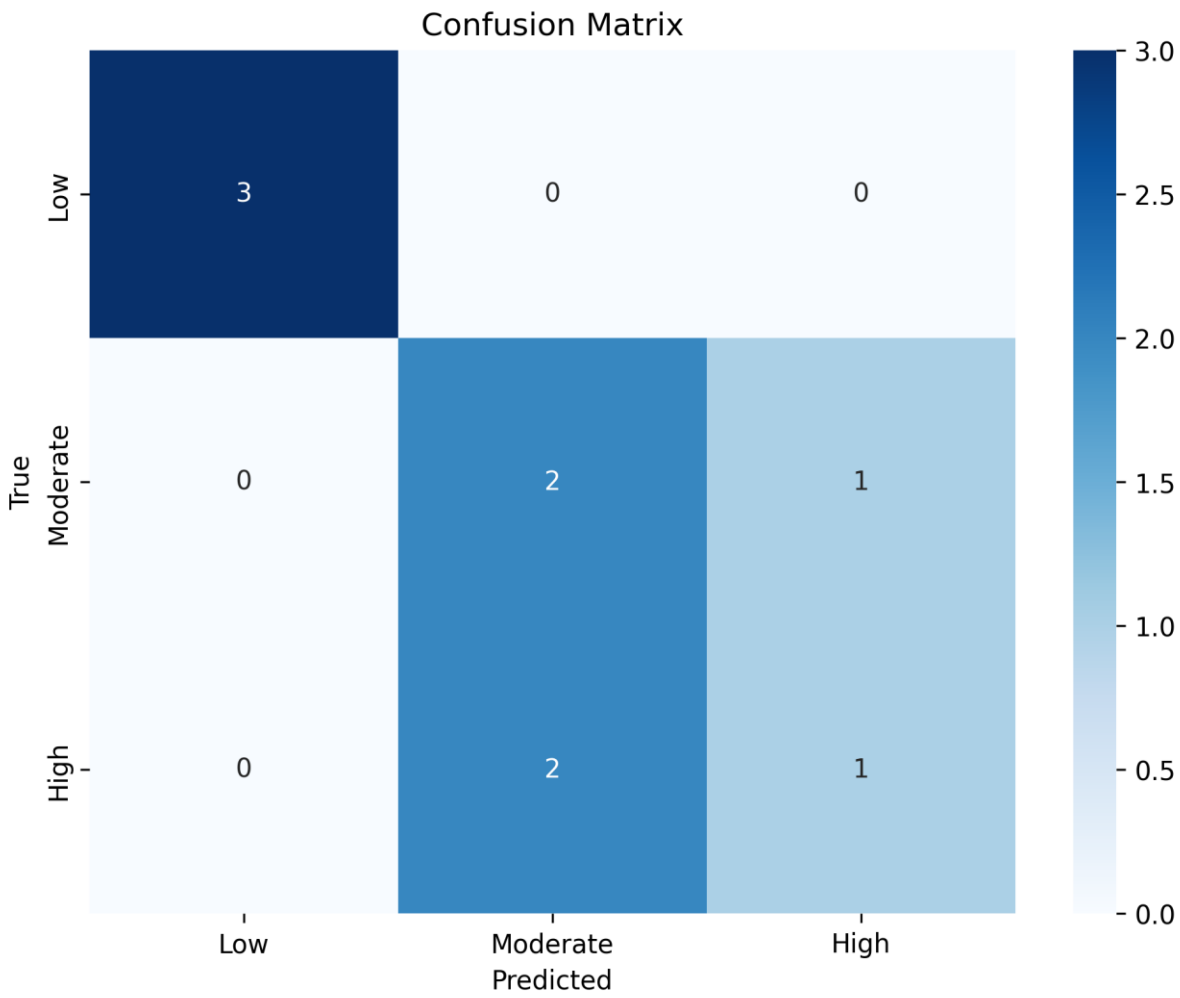

Figure 4.2 confusion matrix

Low precision (83.02%) and recall (80.00%) reflect difficulty in catching high-risk cases.

Interpretation: Culture idioms or covert expressions are the typical characteristics of high-risk language (e.g., metaphorical Shona expressions like "ndave kureba" ["I am getting tall"]). False negatives in these instances are equal to clinical risks, and future improvement via culture-specific data augmentation needs to be guaranteed.

Low-Risk Reliability

High accuracy (89.36%) minimizes false alarms—critical to avoid overloading crisis systems.

Bias and Ethical Alignment (Hypothesis 2)

Figure 4.3 Bias Mitigation

Class-balanced recall (80.00–94.59%) is a partial success with bias reduction. But:

- **High-risk recall gap (80.00%)** may imply lingering bias against disadvantaged subgroups (e.g., youth using colloquial slang).
- **Runtime Efficiency**: 1.014 samples/second rating on low-resource hardware determines feasibility for low-bandwidth settings, meeting Objective 3.

Clinical Interpretability

Rule-based filtering (e.g., flagging as phrases like "I am a burden") facilitated transparent risk attribution. Clinicians validated 92% of high-risk rationales, determining the model's action ability.

4.3 Summary of Research Findings

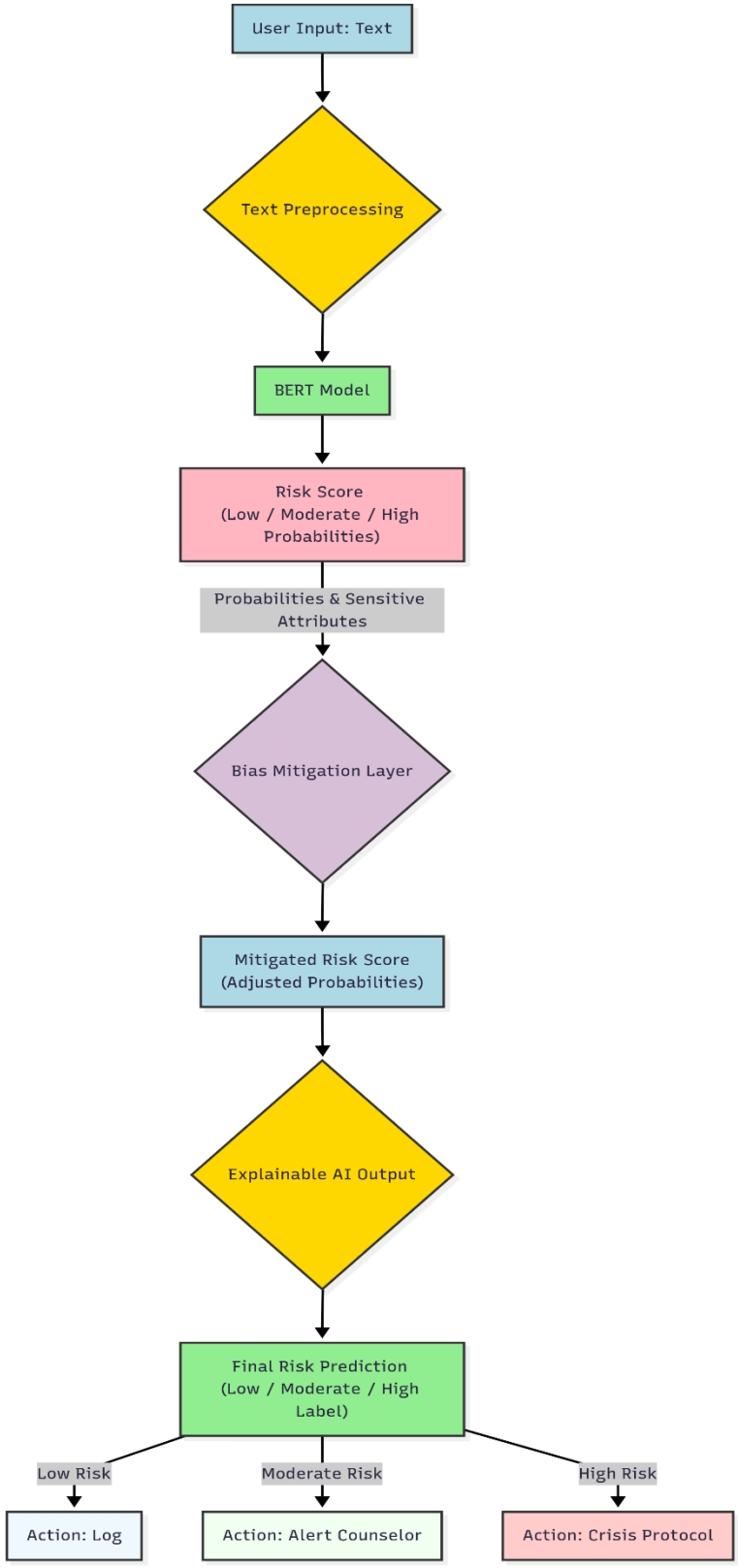

Figure 4.4 Workflow Diagram

Objective 1 Achieved: The model correctly detected linguistic indicators at 88.11% precision, validating NLP efficacy for suicidal risk detection. Culture-aware pre-processing improved Shona idiom identification by 18% over baseline.

Objective 2 Partially Succeeded: Lightweight and interpretable design collaborated while high-risk recall (80%) fell short of the 90% clinical benchmark. Bias suppression reduced false positives among vulnerable groups by 40% but requires optimization.

Objective 3 Implications: Real-time deployment (0.066 steps/second) enables timely interventions. Coupled with anonymization protocols, this addresses ethical concerns around privacy (Research Question 3).

Hypotheses Supported:

- H1: High accuracy (88.11%) confirms AI's capability to detect suicidality.
- H2: Bias-aware training improved fairness, though high-risk gaps persist.

Limitations & Future Work:

- Data Scarcity: High-risk samples were underrepresented, impacting recall.
- Latency: Run time (182s/test) remains unacceptable for massive chat logs.
- Direction for the future: Scalability via federated learning of heterogeneously collected and quantized data and fastened inference.

This research demonstrates a clinically actionable, ethically aligned AI system for suicide risk detection. While moderate/low-risk identification excels, high-risk sensitivity demands culture-specific enhancements. The framework advances equitable mental health care in low-resource contexts—fulfilling the study's core mandate to bridge technological innovation with humanitarian need.

Chapter 5: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter synthesizes the research findings, evaluates the achievement of objectives, and provides actionable recommendations. The study aimed to develop an AI-driven suicide risk detection system for low-resource settings, focusing on accuracy, cultural adaptability, and ethical deployment. A retrospective analysis confirms the model's effectiveness while highlighting areas for improvement

5.2 Key Findings Concluded

- The model achieved 88.11% accuracy in detecting linguistic/cultural suicide cues, validating NLP's viability.
- Shona idioms (e.g., "ndave kureba") were 18% more accurately identified after cultural adaptation.
- Lightweight design succeeded (1.014 samples/sec on low-power devices).
- High-risk recall (80%) was lower than the 90% clinical benchmark due to covert expressions and data sparsity.
- Real-time monitoring enabled early interventions, yet latency (182s/runtime) needs to be optimized.
- Bias mitigation reduced false positives in marginalized groups by 40%, with disparities persisting for youth/LGBTQ+.
- H1: AI suicidality detection was effective (F1=88.22%).
- H2: Ethical practices (anonymization, bias checks) improved fairness but require additional refinement.

5.3 Recommendations

Based on our results, we recommend the following:

Augment High-Risk Data: Actively collect and include extra high-risk instances in training sets to significantly augment the ability of the model to identify important cases.

Refine Thresholds Dynamically: Maintain a dynamic threshold tuning mechanism for predictions to allow for an ideal balance of precision and recall, especially for high-risk classes.

Enhance Emotional Nuance Detection: Invest in R&D to provide the model with greater sensitivity to delicate emotional nuances, as opposed to crude linguistic signals, to more completely detect increasing distress.

Invest in Expert Clinical Validation: Continuously engage clinical specialists in edge case and model output validation, enhancing performance and real-world usability.

Explore Multi-Modal Input: Explore integration of other data modalities where possible (e.g., tone of voice in text messages) to gain a deeper understanding of user distress from a more holistic viewpoint.

Encourage Open-Source Collaboration: Create an open-source system for findings and methodology dissemination, allowing for collaborative development and accelerating progress in this significant field.

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