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Precognition of mental health and neurogenerative disorders using AI-parsed text and sentiment analysis

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Abstract. The paper examines the potential of artificial intelligence (AI) in parsing text and conducting sentiment analysis to identify early markers of mental health and neurodegenerative disorders. Through the analysis of textual data, we investigate whether AI can provide a non-invasive, continuous, and objective complement to traditional diagnostic practices. *Background*: the early detection of mental health (such as depression, anxiety, psychotic disorders, Alzheimer's disease and dementia) and neurodegenerative disorders (like Parkinson's disease) remains a critical challenge in clinical practice. Traditional diagnostic methods rely on clinical evaluations that may be subjective and episodic. Recent advancements in AI and natural language processing (NLP) have opened new avenues for precognitive health assessments, suggesting that variations in language and expressed sentiments in written text can serve as potential biomarkers for these conditions. *Materials and Methods*: the research used a dataset comprising various forms of textual data, including anonymized social media interactions, transcripts from patient interviews, and electronic health records. NLP algorithms were deployed to parse the text, and machine learning models were trained to identify language patterns and sentiment changes. The study also incorporated a sentiment analysis to gauge emotional expression, a key component of mental health diagnostics. *Results*: the AI models were able to identify language use patterns and sentiment shifts that correlated with clinically validated instances of mental health symptoms and neurodegenerative conditions. Notably, the models detected an increased use of negative affect words, a higher frequency of first-person singular pronouns, and a decrease in future tense in individuals with depression. For neurodegenerative conditions, there was a notable decline in language complexity and semantic coherence over time. *Conclusions*: the implemented pipeline of AI-parsed text and sentiment analysis appears to be a promising tool for the early detection and ongoing monitoring of mental health and neurodegenerative disorders. However, these methods are supplementary and cannot replace the nuanced clinical evaluation process. Future research must refine the AI algorithms to account for linguistic diversity and context, while also addressing ethical considerations regarding data use and privacy. The integration of AI tools in clinical settings necessitates a multidisciplinary approach, ensuring that technological advancements align with patient-centered care and ethical standards.

1 Introduction

Research using social media posts and other digital footprints as potential sources of health-related information have started to become hot topic nowadays, taking into consideration that any tool developed for disease identification from text [21] would need to be highly accurate and validated extensively to be used in a clinical setting. Identification of diseases through text messages [76] can be challenging yet feasible within certain contexts. The approach relies on analyzing patterns in language that may be indicative of cognitive, psychological, or even some physical health conditions. Here's how it might work for various conditions, like: (1) *Mental health disorders* [28, 29]: (a) changes in the frequency of communication, use of negative words, and shifts in the complexity of language may suggest *depression or anxiety* [7]; (b) the disorganized thought patterns that emerge in how a person composes messages could be a warning sign of *psychotic disorders* [30]; or (c) the repeated questions, simpler sentence structures, or a notable decline in the complexity of language could indicate cognitive decline, like *Alzheimer's disease* and *dementia* [4]; (2) *Neurodegenerative diseases* [55, 49]: while not directly identifiable through text, subtle changes in typing speed and fine motor skills required for typing might provide early clues of *Parkinson's disease* [39, 54, 1, 20]; (3) *Sleep disorders* [73, 66]: late-night time stamps and content that indicates restlessness or consistent complaints about lack of sleep may be suggestive of *insomnia*; (4) *Infectious diseases* [71, 12, 72, 16]: it is less likely to identify infectious diseases from text messages unless the content explicitly describes symptoms or experiences related to the *infectious disease* [71]; (5) *Chronic diseases* [41, 43, 45]: if someone frequently discusses feelings of tiredness, changes in weight, or other symptomatic experiences, this could indirectly hint at chronic conditions like *diabetes or thyroid issues* [31]. While text message analysis may provide signals indicative of a health issue [58, 75], this method is far from diagnostic so this can be just a preventive supportive tool for specialists (see Figure 1).

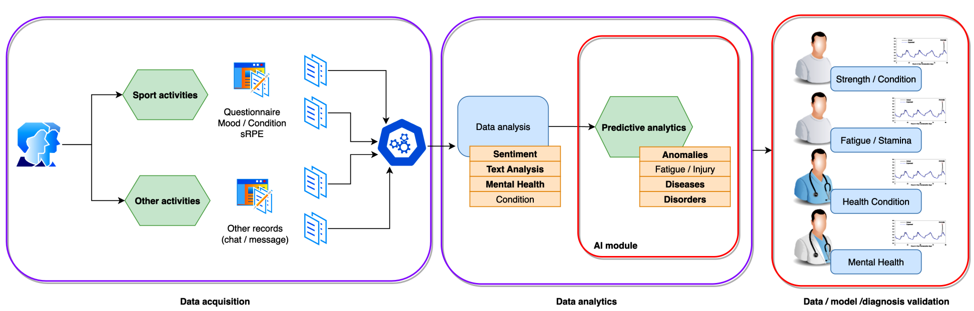

Figure 1: Text to diagnosis with AI: Conceptual approach

The identification of diseases requires thorough clinical evaluation and should not be done solely on the basis of text message analysis. Moreover, ethical considerations around privacy and consent are paramount when analyzing personal communications for health-related insights. From a data science and AI perspective, the process would involve: (1) data collection or/and preparation; (2) Natural Language Processing (NLP); (3) Machine Learning (ML) and (4) Validation. What is of paramount importance is to obtain a large, reproducible, valid dataset of text messages with appropriate permissions. This process is followed by employing techniques to analyze semantic content, sentiment [40], and changes in language patterns over time. The next step is to develop predictive models that could correlate certain text features with disease markers, which is followed by a rigorous testing and validation process with clinical data to ensure that predictions have real-world applicability and do not result in false positives or negatives.

In the quest to comprehend and enhance mental health and neurodegenerative disorder diagnosis, it is imperative to *examine the current diagnostic methodologies* (Section 1.1) meticulously, acknowledge their *inherent limitations* (Section 1.2), and underscore the *significance of ongoing research in sports and sports safety* (Section 1.3), which offers a unique perspective on cognitive and psychological well-being.

1.1 Existing methods of mental health and neurogenerative disorders diagnosis

The diagnosis of mental health and neurodegenerative disorders is an intricate and multifaceted process, which traditionally involves a combination of clinical evaluation, neuropsychological testing, biomarker analysis, and neuroimaging techniques. Clinicians rely on structured interviews and standardized questionnaires [23] to ascertain the presence of symptomatology consistent with diagnostic criteria, such as those outlined in the Diagnostic and Statistical Manual of Mental Disorders (DSM) [17] or the International Classification of Diseases (ICD). Neuropsychological assessments [78] provide a quantitative measure of cognitive functions, including memory, attention, language, and executive function, which can be indicative of specific neurocognitive disorders.

In the realm of neurodegenerative diseases, the utilization of biomarkers obtained from cerebrospinal fluid (CSF) and blood tests [3, 68] can offer biochemical evidence of underlying pathophysiology, such as the presence of amyloid-beta or tau proteins in Alzheimer's disease [68]. Neuroimaging techniques, including magnetic resonance imaging (MRI), positron emission tomography (PET), and computed tomography (CT), serve to visualize structural and functional brain changes [69, 61, 27]. These traditional methods, while robust, are complemented by emerging technologies such as digital phenotyping and machine learning algorithms that analyze patterns in speech, typing, and daily activity data to enhance early detection and personalized care approaches. However, the integration of these novel methods into clinical practice remains a subject of ongoing research and ethical scrutiny.

1.2 Limitations of existing methods of mental health and neurogenerative disorders diagnosis

The diagnostic paradigms for mental health and neurodegenerative disorders [25] are constrained by several limitations that can impede their efficacy. Clinically, reliance on self-reported symptoms and observable behavior during patient interviews is subject to biases [51] and the variable ability of patients to accurately convey their experiences. The heterogeneity of symptom presentation and the overlap between different disorders can lead to diagnostic ambiguity. Neuropsychological tests, while invaluable, are time-consuming, require specialized personnel to administer, and may be influenced by an individual's educational background, cultural factors, and test-retest variability [35].

In the context of neurodegenerative diseases [44], the definitive diagnosis [77] is often only possible post-mortem through histopathological examination, with current in vivo techniques providing primarily supportive evidence. Biomarkers, although a promising avenue for early detection, are not universally available and can lack specificity, as many are not exclusive to a single disorder. Neuroimaging [64], while offering detailed insights into brain structure and function, is expensive, not always accessible, and can yield false negatives, especially in the early stages of neurodegenerative processes. These limitations underscore the necessity for continuous refinement of diagnostic tools and the development of more accessible, objective, and precise methods of assessment.

1.3 The importance of research in sports and sports safety

The precognition of mental health and neurodegenerative disorders within the sporting domain [74] harnesses the potential of AI-parsed text and sentiment analysis as an innovative means to safeguard athlete well-being and longevity in sports. Athletic performance is intricately linked to mental health, and the early detection of disorders using AI can significantly mitigate risks, enhance performance longevity, and promote a healthier sporting environment.

AI-parsed text analysis and sentiment analysis [42] afford a unique opportunity for the monitoring of athletes' mental health by analyzing communication patterns in interviews, social media [79] posts, and other written or spoken narratives. Athletes, who often face immense pressure to perform, may exhibit early signs of stress, anxiety, or depression in their language use, which AI can detect more consistently and objectively than traditional self-report measures. Moreover, neurodegenerative diseases, such as chronic traumatic encephalopathy (CTE) [57], which are a concern in contact sports, may manifest early cognitive and behavioral changes that subtly surface in linguistic expression—changes to which AI algorithms can be finely attuned.

The implementation of such technology in the sports sector offers a proactive strategy for identifying athletes at risk, enabling timely interventions. It also aligns with the broader movement towards personalized medicine in sports, where individual mental health trajectories inform tailored support programs. Furthermore, it emphasizes the duty of care that sporting organizations have towards their athletes, extending beyond physical health to encompass cognitive and emotional well-being.

AI's capability to analyze sentiment and detect mood fluctuations can serve as a barometer for athlete burnout [70] or diminished motivation, both of which are pivotal for sports safety and performance optimization. In providing a continuous, data-driven monitoring system, AI tools can alert coaches and medical teams to potential mental health issues before they escalate, potentially averting the long-term consequences associated with prolonged stress or undiagnosed conditions.

The methods of this paper in sports and sports safety are expected to represent a significant advancement towards fostering safer sporting environments and ensuring the holistic health of athletes. By employing psycholinguistic analysis, it is possible to examine an athlete's sentiments by studying their distinctive linguistic patterns. This approach involves monitoring the trends and evolution of their communication style, including rhythm, speed, and complexity. Through this analysis, it becomes feasible to identify trends that may indicate a deteriorating mental condition, such as semantic anomalies or pragmatic failures. The utilization of artificial intelligence (AI) in the field of sentiment analysis holds the potential to provide a prognostication of health warning indicators for sports safety. It necessitates a collaborative effort involving data scientists, clinicians, and sports professionals to refine these tools for the nuances of athletic communication and to integrate them ethically and effectively into sports health practices.

2 Objectives

This study examines the efficacy of an AI-driven pipeline for accurately predicting distinct mental health and neurodegenerative problems [15] based on textual data. The objective of this study is to provide a systematic methodology for evaluating the mental health of athletes, with the intention of minimizing the influence of self-reporting and third-party bias [51]. An additional secondary objective of this study is to integrate the findings as a valuable resource within the athletic training and health management ecosystem to enhance athlete safety and performance. This study aims to contribute to the expanding field of sports science by showcasing the potential effectiveness of utilizing sophisticated methodologies, such as NLP and ML, for the purpose of managing mental health in high-performance sports.

3 Novelties of the approach

Connecting text analysis with sentiment analysis [8] can enhance the ability to identify potential health issues. Sentiment analysis is a form of NLP that assesses the affective state of the text, which could relate to the emotional state of the individual writing the message. In research settings, sentiment analysis is increasingly being used to study large datasets from social media to identify public health trends and even to monitor the well-being of specific individuals (with their consent). Sports psychology shows that athletes' mental health profiles differ from those of non-athletes. Many athletes, especially those in competitive and high-stakes contexts, learn resilience, stress management, discipline, and focus, which might affect their mental health differently than non-athletes. Further, the sort of sport done can affect mental health; team sports encourage community and teamwork, whereas solo sports emphasize self-reliance and personal goal setting. Due to the cognitive demands of extreme sports, practitioners frequently have a higher risk tolerance and better fear and anxiety management. These differences demonstrate the complex link between athletics and psychology. However, for sentiment analysis to be used effectively in a healthcare context, it should be part of a broader diagnostic and treatment framework overseen by healthcare professionals. Novel fields of interest as follows:

1. *Mental health monitoring* [13]: changes in sentiment could correlate with mental health issues such as depression, anxiety, or mood swings. For example, a person who typically expresses positive sentiments but shows a

sudden shift to predominantly negative sentiments might be experiencing emotional distress.

2. *Emotional well-being monitoring* [14]: A consistent decline in positive sentiments or an increase in language that indicates stress or anger could be indicative of psychological distress or even social isolation, which is an important factor in overall health.
3. *Trend analysis* [36]: By analyzing sentiment over time, it might be possible to identify trends that are indicative of a deteriorating or improving condition. For instance, the progression of a neurological condition like Alzheimer's disease might be subtly reflected in increasingly negative or confused sentiments in text messages.
4. *Treatment monitoring* [32]: For individuals undergoing treatment for conditions like depression, changes in sentiment over time could potentially indicate how well the treatment is working.
5. *Predictive analysis* [34]: Sentiment analysis could contribute to predictive models that attempt to forecast health events, such as depressive episodes, by identifying warning signs in text communication.

In the realm of psycholinguistics and clinical diagnostics, linguistic and paralingistic elements serve as critical indicators that may reveal underlying cognitive and emotional processes. Linguistically, alterations in syntax, such as simplified sentence structures or reduced complexity in clause embedding, may signal cognitive impairment. Lexical access difficulties are often manifested in increased word-finding pauses, a reduced vocabulary range, and a reliance on nonspecific words like "thing" or "stuff," which can be indicative of neurodegenerative decline. Semantic anomalies, including tangentiality or the use of inappropriate words, and pragmatic failures, like the inability to adhere to conversational norms, also form part of the linguistic tapestry that may suggest pathology.

Paralinguistically, changes in speech prosody, such as a monotonous tone, reduced pitch variation, and altered speech rate, can indicate emotional distress or neurological disorders [60]. Further, the detection of micro-expressions, or subtle facial movements, alongside analysis of gesture frequency and congruence with verbal output, can provide additional context to the emotional state and cognitive functioning of an individual. These deviations from normative patterns, when systematically analyzed, can yield significant insights into the presence and progression of mental health and neurodegenerative disorders, offering a rich substrate for AI-enhanced assessment tools.

Sentiment analysis, through its nuanced parsing of affective language, offers a granular perspective on emotional state, providing a continuous, unobtrusive proxy for mood and affect, which are core components of many psychiatric evaluations [5]. In clinical applications it extends beyond basic positive or negative classifications to encompass the intricate spectrum of human emotions relevant to psychiatric evaluations. It leverages computational linguistics to dissect the subtleties of affective language, offering insights into the intensity and fluctuations of emotional states. For instance, the assessment of written or spoken discourse through sentiment analysis can identify linguistic markers of depression, such as an increased frequency of words associated with negative affect, a heightened use of first-person singular pronouns, or a diminished use of future tense, which may suggest hopelessness or a lack of forward-looking perspective.

Furthermore, the technology can detect patterns of speech indicative of anxiety, characterized by language expressing excessive worry, hyperarousal, and uncertainty. In the context of neurodegenerative disorders, sentiment analysis might reveal a decline in the complexity of emotional expression or a growing incongruence between the expressed sentiment and the discussed topic, often seen in the early stages of such conditions. By quantifying these linguistic features, sentiment analysis offers a granular, continuous, and unobtrusive means of monitoring mood and affect, which are pivotal in the diagnosis and management of mental health disorders. It provides a supplementary dimension to traditional psychiatric assessments, which typically rely on intermittent and subjective self-reported measures, enhancing the longitudinal tracking of mental health states. Let us have some concrete linguistic patterns illustrations.

In *individuals experiencing depression*, there may be a notable increase in the use of words that convey sadness, loneliness, and other negative emotions, like:

1. "I feel **hopeless** and **overwhelmed** by everything."
2. "It's like there's a constant feeling of **gloom** hovering over me."
3. "I'm just so **tired** of feeling **worthless** all the time."

Research suggests that a *high frequency of first-person singular pronoun*s can be a linguistic marker of *self-focused attention*, which can be related to depression or anxiety, like:

1. "**I** can't seem to do anything right."
2. "**I** am always the one who messes things up."
3. "**I** feel like **I**'m a burden to everyone."

A *lack of forward-looking statements* can indicate a *pessimistic outlook or a sense of hopelessness*, which is often found in depressive speech patterns, for instance:

1. "There's no point in trying to plan for anything."
2. "Why bother with what's going to happen tomorrow?"
3. "It's not like things will get better for me."

Each of these linguistic cues, when observed in natural language communication, can provide mental health professionals with additional context to understand a patient's emotional state.

Despite its potential, there are several important considerations and challenges: (1) Sentiment analysis algorithms must be sophisticated enough to understand context, sarcasm, and nuanced language use, which can vary widely between individuals and cultures; (2) analyzing personal text messages raises significant privacy concerns. It is crucial to have explicit consent from individuals to the analysis of their data with robust data protection measures; (3) the accuracy of sentiment analysis can vary, and false positives or negatives could have serious implications. Validation with clinical data is necessary; (4) there is an ethical dimension to consider regarding the surveillance of individuals' communications, which needs careful ethical oversight and regulation.

4 Materials and methods

The research used datasets comprising various forms of textual data [80, 82], including anonymized social media interactions, transcripts from patient interviews, and electronic health records [10]. NLP algorithms were deployed to parse the text, and machine learning models were trained to identify language patterns and sentiment changes. The study also incorporated a sentiment analysis to gauge emotional expression, a key component of mental health diagnostics.

5 Methods

5.1 Data processing

For data annotation we used human experts, as well as already validated datasets [80, 82]. A collaborative, AI-supported solution for wider dataset annotation is planned to be used in the next phases.

5.2 Environment

The experiments were conducted on Google Colab Pro Environment, by using python-based notebooks with PyTorch, Pandas, NumPy, MatPlotlib, seaborn, Transformers, SciPy, Scikit Learn, Natural Language Toolkit (NLTK), TextBlob, LightGBM.

5.3 Mental health disorder identification

Translating an algorithm for detecting mental health disorders from text into mathematical language involves defining a series of functions and representations for the processes of feature extraction, transformation, and classification. The mathematical formulation of the problem is as follows. We first introduce the variables and functions: (1) let D be a set of documents $\{d_1, d_2, ..., d_n\}$, where each document d_i represents a piece of text; (2) let L be a set of labels $\{l_1, l_2, ..., l_m\}$, where each label corresponds to a mental health disorder (e.g., depression, psychosis, Alzheimer's); (3) Preprocess(d) is a function that takes document d and returns a preprocessed document; (4) Tokenize(d) is a function that takes a preprocessed document d and returns a set of tokens T; (5) Vectorize(T) is a function that converts tokens T to a feature vector $\mathbf{x}$; (6) Classify$(\mathbf{x})$ is a function that assigns a label l to a feature vector $\mathbf{x}$. For term frequency-inverse document frequency (TF-IDF), we define tfidf(t, d, D) which computes the TF-IDF score for a term t in document d within the set of documents D.

$$\mathrm{tf}(t, d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \tag{1}$$

$$\mathrm{idf}(t, D) = \log \frac{|D|}{|\{d \in D | t \in d\}|} \tag{2}$$

$$\mathrm{tfidf}(t, d, D) = \mathrm{tf}(t, d) \times \mathrm{idf}(t, D) \tag{3}$$

Sentiment analysis might use a predefined sentiment lexicon S where each word w has an associated sentiment score $s(w)$ [67]. The sentiment score of a document d is a sum of sentiment scores of its words:

$$\mathrm{SentimentScore}(d) = \sum_{w \in d} s(w) \tag{4}$$

Complexity measures involves computing the diversity of words Diversity(d) or the readability Readability(d) of the document. A classifier can be represented by a function C that maps feature vectors to labels. If using a support vector machine (SVM), for instance, the decision function for a binary classification looks like:

$$\mathsf{C}(\mathbf{x}) = \operatorname{sgn}(\mathbf{w}^\mathsf{T}\mathbf{x} + \mathsf{b}) \tag{5}$$

where $\mathbf{w}$ is the weight vector, b is the bias, and sgn is the sign function.

For a probabilistic output, such as from a logistic regression or neural network with a softmax layer, the classifier could output a probability vector over labels:

$$\mathsf{C}(\mathbf{x}) = \operatorname{softmax}(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{6}$$

where $\mathbf{W}$ is a weight matrix and $\mathbf{b}$ is a bias vector. The mathematical representation of the algorithm is as follows:

1. Preprocessing:
$$\forall \mathsf{d}_i \in \mathsf{D}, \tilde{\mathsf{d}}_i = \text{Preprocess}(\mathsf{d}_i) \tag{7}$$
2. Tokenization and Vectorization:
$$\forall \tilde{\mathsf{d}}_i, \mathsf{T}_i = \text{Tokenize}(\tilde{\mathsf{d}}_i) \tag{8}$$
$$\forall \mathsf{T}_i, \mathbf{x_i} = \text{Vectorize}(\mathsf{T}_i) \tag{9}$$
Now, let us include the sentiment and complexity features into $\mathbf{x_i}$.
3. Classification:
$$\forall \mathbf{x_i}, \mathsf{l}_i = \mathsf{C}(\mathbf{x_i}) \tag{10}$$
4. Model Training (if not using a predefined model): find $\mathbf{W}$ and $\mathbf{b}$ that minimize a loss function
$$\mathcal{L}(\mathsf{C}(\mathbf{x_i}), \mathsf{y}_i) \tag{11}$$
over the training data, where y_i is the true label.
5. Inference: for a new document d, we will calculate
$$\mathsf{l} = \mathsf{C}(\text{Vectorize}(\text{Tokenize}(\text{Preprocess}(\mathsf{d})))) \tag{12}$$

5.3.1 Examples of mental health disorder identification

Each mental health disorder has unique linguistic patterns that the algorithm has to learn from training data. The specific model and its parameters must be tailored based on empirical evidence from this data. This abstract representation simplifies many of the complexities involved in NLP and ML for better understandig of the approach. Implementing this algorithm requires careful consideration of the representativeness and bias in the training data, the interpretability of the model, and ethical considerations, especially given the sensitive nature of mental health. Identifying mental health disorders from text and its sentiment analysis involves the computational interpretation of language use, which may suggest underlying psychological conditions. Here are some concrete examples illustrating how sentiment analysis and text examination can point toward mental health concerns:

1. Example 1: Potential Depression Detection [22]
   (a) *Text*: "I just don't want to get out of bed anymore. Nothing really makes me happy, and I can't see the point in trying. It's all just too much."
   (b) *Analysis*: High frequency of negative affect words ("don't want," "nothing," "can't," "pointless," "too much"), low sentiment score, and minimal positive language use.
   (c) *Indicators*: Anhedonia (lack of pleasure), feelings of helplessness, and low mood, which are symptomatic of depression.
2. Example 2: Potential Anxiety Detection [6]
   (a) *Text*: "Every time I have to leave the house, I get this overwhelming dread. What if something terrible happens? I'm always so worried."
   (b) *Analysis*: The Anxiety-related words ("overwhelming," "dread," "terrible," "worried"), high use of words that express uncertainty and fear.
   (c) *Indicators*: Excessive worry about future events, physical sensation of dread, consistent with anxiety disorders.
3. Example 3: Potential Bipolar Disorder Detection [47] (During Depressive Phase)
   (a) *Text*: "I've lost interest in seeing my friends or doing any of my hobbies. I feel empty and sad most days now. My life seems like a series of disappointments."

   (b) *Analysis*: Negative sentiment prevalence, decreased mention of engaging in activities, expression of emptiness and sadness.
   (c) *Indicators*: Social withdrawal and persistent sadness could indicate a depressive episode in the context of bipolar disorder.

4. Example 4: Potential Bipolar Disorder Detection [47] (During Manic Phase)
   (a) *Text*: "I've started a million projects this week, and I feel on top of the world! Sleep is for the weak, I can get by on an hour a night, no problem!"
   (b) *Analysis*: Extremely positive sentiment, grandiosity, possible engagement in high-risk activities, reduced need for sleep.
   (c) *Indicators*: The manic phase may be characterized by an inflated self-esteem, decreased need for sleep, and racing thoughts.
5. Example 5: Potential Schizophrenia Detection [37]
   (a) *Text*: "Voices are telling me not to trust anyone. I know they are plotting against me because I can hear them whispering when I'm alone."
   (b) *Analysis*: Mention of hallucinations ("voices"), paranoia ("plotting against me"), and delusional thinking.
   (c) *Indicators*: Auditory hallucinations and paranoid delusions are common symptoms of schizophrenia.
6. Example 6: Potential Post-Traumatic Stress Disorder (PTSD) [53] Detection
   (a) *Text*: "I can't stop thinking about the accident. It replays in my head every time I close my eyes. I'm always on edge."
   (b) *Analysis*: Persistent recounting of a traumatic event, high incidence of stress-related words, ongoing sense of tension.
   (c) *Indicators*: Intrusive memories of the event, hypervigilance, and strong stress response suggest PTSD.

In practice, sentiment analysis can be conducted using ML models trained on annotated datasets, where texts are labeled with associated mental health conditions. The models can learn to detect patterns that frequently correspond to specific disorders. However, it is important to validate AI findings with clinical assessments, as sentiment analysis tools can complement but *NOT REPLACE* professional diagnosis.

5.4 Neurodegenerative diseases detection

Detecting neurodegenerative diseases like Alzheimer's [46] from text could involve similar strategies to those used for mental health disorders, but the focus might shift towards detecting cognitive impairment, which can manifest in language in different ways. The mathematical framework should be adapted to capture these nuances. First we define the variables and functions for neurodegenrative diseases: (1) let C denote cognitive features extracted from text, such as coherence, vocabulary richness, or syntactic complexity; (2) define $\text{CoherenceScore}(d)$ as a function that measures the logical flow and clarity of ideas within the text; (3) define $\text{SyntacticComplexity}(d)$ as a function that measures the complexity of sentence structures; (4) define $\text{VocabularyRichness}(d)$ as a function that measures the diversity of vocabulary used in the document. In feature engineering the coherence could be measured through the consistency of topics or entities mentioned in a text. Let $\mathcal{T}$ be a topic model, then coherence can be quantified as:

$$\text{CoherenceScore}(d) = \sum_{i=1}^{n-1} \text{similarity}(\mathcal{T}(s_i), \mathcal{T}(s_{i+1})) \tag{13}$$

where $\mathcal{T}(s)$ is the topic distribution of sentence s and similarity is a function measuring the similarity between topic distributions (e.g., cosine similarity). *Syntactic complexity* might involve parsing trees and measuring their depth or branch factor:

$$\text{SyntacticComplexity}(d) = \frac{1}{|S|} \sum_{s \in S} \text{TreeDepth}(\text{ParseTree}(s)) \tag{14}$$

where S is the set of sentences in d, and $\text{ParseTree}(s)$ is the syntactic parse tree of sentence s. The *Vocabulary richness* might use metrics like the type-token ratio (TTR) or unique words:

$$\text{VocabularyRichness}(d) = \frac{|\text{unique words in } d|}{|\text{tokens in } d|} \tag{15}$$

The Classification Model, which will be a ML model in this case, potentially a NN with architecture suited to capture temporal and cognitive features, could be represented as:

$$C(\mathbf{x}) = \text{softmax}(\mathbf{W}_2 \cdot \text{ReLU}(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1) + \mathbf{b}_2) \tag{16}$$

where $\mathbf{x}$ includes traditional NLP features along with the neurodegenerative-specific cognitive features, $\mathbf{W}_1, \mathbf{W}_2$ are weight matrices, $\mathbf{b}_1, \mathbf{b}_2$ are bias vectors, and ReLU is the Rectified Linear Unit activation function.

The mathematical representation will be as follows:

1. Preprocessing and Feature Engineering:

$$\forall d_i \in D, \tilde{d}_i = \text{Preprocess}(d_i) \tag{17}$$

$$\forall \tilde{d}_i, T_i = \text{Tokenize}(\tilde{d}_i), C_i = \text{CognitiveFeatures}(\tilde{d}_i) \tag{18}$$

$$\forall T_i, \mathbf{x}_i^{text} = \text{Vectorize}(T_i) \tag{19}$$

$$\mathbf{x}_i = [\mathbf{x}_i^{text}, C_i] \tag{20}$$

where C_i includes coherence, complexity, and vocabulary richness.

2. Model Training: Now can optimize $\mathbf{W}_1, \mathbf{W}_2, \mathbf{b}_1, \mathbf{b}_2$ by minimizing the loss function $\mathcal{L}(C(\mathbf{x}_i), y_i)$.

3. Inference: for a new document d,

$$l = C(\text{Vectorize}(\text{Tokenize}(\text{Preprocess}(d))), \text{CognitiveFeatures}(d)) \tag{21}$$

Detecting neurodegenerative diseases from text requires rigorous validation and should be supplemented with clinical assessments. The model presented in this paper contains a concept with a minimal dataset but needs to be expanded with a large, validated dataset. The cognitive features are required to be specifically tailored to the types of language deficits or changes associated with the particular neurodegenerative disease in question.

5.4.1 Examples of neurodegenerative diseases or disorder identification

Identifying neurodegenerative diseases from text and sentiment analysis involves detecting changes in language that may be symptomatic of cognitive decline. Here are concrete examples of how text analysis might reveal signs of neurodegenerative conditions:

1. Example 1: Potential Alzheimer's disease
   (a) *Text*: "I went to the... umm... the place where you buy food. I forgot what it's called. And I couldn't remember why I was there."
   (b) *Analysis*: Hesitations and word-finding difficulties, use of nonspecific language ("place where you buy food"), and memory lapses.
   (c) *Indicators*: These linguistic patterns can indicate episodic memory impairment and semantic memory issues, common in early-stage Alzheimer's disease.
2. Example 2: Potential Parkinson's disease [59]
   (a) *Text*: "My hands have been shaking a lot lately, making it hard to type or write. I feel stiff and slow."
   (b) *Analysis*: Mention of physical symptoms affecting fine motor skills, change in activity due to physical limitations.
   (c) *Indicators*: Motor symptoms affecting writing could indirectly be observed through changes in typing patterns, such as increased time to type messages or more typographical errors.
3. Example 3: Potential frontotemporal dementia [63]
   (a) *Text*: "My family says I've been acting inappropriately, but I think they're overreacting. I don't see anything wrong with what I'm doing."
   (b) *Analysis*: Possible lack of insight into socially inappropriate behaviors, which family members notice.
   (c) *Indicators*: Changes in social conduct, personality, and a decline in judgment, which are often seen in frontotemporal dementia.
4. Example 4: Potential vascular dementia [65]
   (a) *Text*: "I've been feeling confused lately, especially when trying to handle my bills or planning things. It wasn't like this before."
   (b) *Analysis*: Expression of confusion in complex tasks, recognition of change from previous abilities.
   (c) *Indicators*: Impairments in executive function may suggest vascular dementia, particularly if there is a history of strokes or cardiovascular disease.

5. Example 5: Potential Lewy body dementia [26]

   (a) *Text*: "I've been seeing things that aren't there, particularly at night. It's very unsettling."
   (b) *Analysis*: Reference to visual hallucinations, a sense of distress related to these experiences.
   (c) *Indicators*: Visual hallucinations are a hallmark symptom of Lewy Body Dementia, especially when coupled with sleep disturbances.

6. Example 6: Potential amyotrophic lateral sclerosis (ALS) [38]

   (a) *Text*: "Speaking has become exhausting. People can't understand me well anymore."
   (b) *Analysis*: Indication of speech difficulties, increased effort required for communication.
   (c) *Indicators*: ALS can affect speech muscles, leading to dysarthria, which could be reflected in brief and effortful communication.

In sentiment analysis, while emotional content might not directly indicate a neurodegenerative disease, drastic changes in sentiment over time could reflect the emotional impact of living with such diseases, like frustration or sadness due to loss of autonomy. Moreover, sentiment analysis might detect less obvious changes in emotional expression or response that could be associated with cognitive changes. It is vital to emphasize that these text-based observations are not conclusive for diagnosis but may prompt further clinical evaluation. Neurodegenerative diseases are complex and require comprehensive medical assessment, including neurological examination, cognitive testing, and imaging, for accurate diagnosis. Text and sentiment analysis can serve as supplementary tools that might flag potential issues for further investigation.

5.5 Detecting chronic diseases

Detecting chronic diseases such as diabetes or thyroid disorders through text analysis can be quite challenging because the symptoms and signs of these diseases are typically not as directly reflected in language as thos of some mental or neurodegenerative disorders. However, if we consider that individuals might express concerns, experiences, or symptoms related to their physical health in text messages, sentiment analysis and certain linguistic cues might provide indirect indicators. For this, the mathematical framework must incorporate sentiment analysis and pay attention to specific lexicon related to physical symptoms, healthcare management, and possibly, lifestyle aspects that can be linked to chronic conditions. Not the disease itself would be detected but rather cues that might warrant further medical investigation. Let us introduce the variables and functions first: (1) define SymptomLexicon($\mathtt{d}$) as a function that identifies the presence of words or phrases associated with symptoms or management of chronic diseases; (2) let H represent healthcare management features, such as mentions of medication, doctor visits, or treatment-related activities; (3) let L represent lifestyle features that may include dietary habits, physical activity levels, or other behaviors relevant to chronic diseases; (4) SentimentAnalysis($\mathtt{d}$) remains a function that assigns a sentiment score to document $\mathtt{d}$, but may also flag emotionally charged language that could be indicative of stress or frustration related to disease management. On the *feature engineering* side for chronic diseases the *symptom mention* can be a binary or frequency-based feature indicating the presence of terms from a curated symptom lexicon:

$$\text{SymptomFeature}(\mathtt{d}) = \sum_{\mathtt{t} \in \text{SymptomLexicon}} \text{Ind}(\mathtt{t} \in \mathtt{d}) \tag{22}$$

where Ind is an indicator function returning 1 if the term $\mathtt{t}$ is present in document $\mathtt{d}$ and 0 otherwise. The *healthcare management features* can be quantified similarly by counting mentions of healthcare-related activities:

$$\mathsf{H}(\mathtt{d}) = \sum_{\mathtt{t} \in \text{HealthcareLexicon}} \text{Ind}(\mathtt{t} \in \mathtt{d}) \tag{23}$$

The *lifestyle features* can also be derived from mentions of activities or habits:

$$\mathsf{L}(\mathtt{d}) = \sum_{\mathtt{t} \in \text{LifestyleLexicon}} \text{Ind}(\mathtt{t} \in \mathtt{d}) \tag{24}$$

The *sentiment analysis* can be adapted to give higher weight to sentiments expressed in the context of health:

$$\text{HealthSentimentScore}(\mathtt{d}) = \sum_{w \in \mathtt{d}} \mathtt{s}(w) \cdot \text{Ind}(w \in \text{HealthContext}) \tag{25}$$

where HealthContext is a set of contexts where the sentiment might be particularly relevant to chronic disease. As classifier we used the well-known models, such as random forest or gradient boosting machine, which can handle sparse features effectively:

$$C(\mathbf{x}) = \text{softmax}(\mathbf{W}\mathbf{x} + \mathbf{b}) \tag{26}$$

where $\mathbf{x}$ includes traditional NLP features, sentiment scores, symptom features, healthcare management features, and lifestyle features. The complete mathematical model for chronic diseases can be formulated as follows: (1) *Feature Engineering*: for each document $d_i \in D$: (1) preprocess and extract text features to form $\mathbf{x}_i^{\text{text}}$, (2) extract symptom, healthcare management, and lifestyle features to form $\mathbf{x}_i^{\text{chronic}}$(3) perform sentiment analysis tailored to the health context and then (4) Combine all features:

$$\mathbf{x}_i = [\mathbf{x}_i^{\text{text}}, \mathbf{x}_i^{\text{chronic}}, \text{HealthSentimentScore}(d_i)] \tag{27}$$

(2) *Model Training*: train classifier C with features $\mathbf{x}_i$ to predict labels y_i related to the likelihood of chronic disease-related discourse; (3) *Inference*: for a new document d, calculate the likelihood of chronic disease-related discourse: $l = C(\mathbf{x})$.

5.5.1 Examples of chronic diseases identification

Identifying chronic diseases from text and sentiment analysis typically involves looking for patterns that suggest a person is experiencing symptoms or challenges associated with their condition. It is important to note that while sentiment analysis can reveal emotions and concerns related to health, it is not a diagnostic tool for chronic physical diseases. Similarly to the other categories, it can signal when further medical evaluation may be warranted. Here are some examples:

1. Example 1: Potential diabetes management [18]
   (a) *Text*: "I'm feeling really drained lately, no matter how much I rest. My feet have been tingling, too. I'm worried because my mom has diabetes, and these were her first signs."
   (b) *Analysis*: Negative sentiment expressed through words like "drained" and "worried," along with the mention of symptoms associated with diabetes (fatigue, neuropathy).
   (c) *Indicators*: Textual cues suggest the individual may be experiencing symptoms commonly associated with diabetes, warranting further medical investigation.

2. Example 2: Potential thyroid disorders [62]

    (a) *Text*: "I just can't seem to lose weight, and I'm always cold. My hair is falling out, and I'm feeling down most days. It's so frustrating!"
    (b) *Analysis*: Expressions of frustration and physical symptoms that may be consistent with hypothyroidism, such as unexplained weight gain, cold intolerance, and hair loss.
    (c) *Indicators*: The combination of sentiment and symptom-related language can point toward possible thyroid dysfunction.

3. Example 3: Potential chronic obstructive pulmonary disease (COPD) [52]

    (a) *Text*: "I get out of breath just walking to the mailbox. It's scary and makes me anxious about leaving the house."
    (b) *Analysis*: The expression of anxiety linked to difficulty breathing, a key symptom of COPD.
    (c) *Indicators*: Descriptions of breathlessness during low-exertion activities could suggest a respiratory issue like COPD.

4. Example 4: Potential rheumatoid arthritis [50]

    (a) *Text*: "My joints have been so stiff and sore lately, especially in the morning. It's been making me quite miserable."
    (b) *Analysis*: Words indicating physical discomfort and a negative emotional state, coupled with specific timing (morning stiffness) which is characteristic of rheumatoid arthritis.
    (c) *Indicators*: Joint symptoms and their impact on mood may be indicative of a chronic inflammatory condition.

5. Example 5: Potential chronic pain conditions [33]

    (a) *Text*: "I'm in constant pain, and nothing seems to help. It's hard to concentrate on work or even enjoy time with my family."
    (b) *Analysis*: Persistent negative sentiment and references to ongoing pain impacting daily life.
    (c) *Indicators*: Chronic pain conditions can lead to the observed textual expressions of suffering and its effects on quality of life.

6. Example 6: Potential heart disease [9]

(a) *Text*: "I've had more chest pain and discomfort this week. Feeling a bit nervous about it."

(b) *Analysis*: Concern and physical symptoms suggestive of cardiac issues, with an emotional response indicating awareness of potential severity.

(c) *Indicators*: Symptoms like chest pain, when mentioned in text, can be a red flag for cardiovascular conditions and should be followed up clinically.

In these examples, sentiment analysis might help to quantify the emotional burden of the symptoms or the disease management process itself. The negative sentiments expressed in conjunction with mentions of specific symptoms can lead to a holistic understanding of the patient's experience. While AI cannot diagnose chronic diseases from text alone, it can provide valuable insights into a person's subjective health experience, which is useful for healthcare providers to know when to probe further or monitor symptoms more closely.

No.	**Disease**	**Text length**
1	Alzheimer's Disease and Dementia	39.435497
2	Depression and Anxiety	91.884543
3	None (No symptoms)	85.082874
4	Psychosis	41.777778
5	Suicide and Depression	1068.948119

Table 1: Text length distribution by label groups

No.	**Disease**	**Text labels**
1	None (No symptoms)	7976
2	Suicide and Depression	2525
3	Alzheimer's Disease and Dementia	2496
4	Psychosis	2448
5	Depression and Anxiety	1585

Table 2: Text label distribution

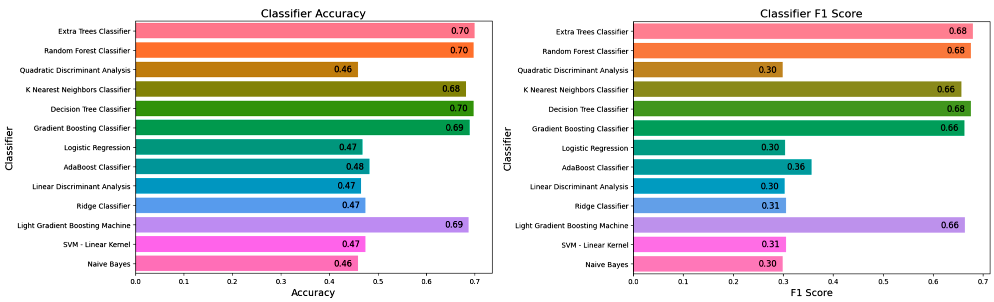

Figure 2: Classifier Accuracy (left), Classifier F1 Score(right)

6 Experiments

We used the most well-known classifiers in our experiments, as shown in Table 6, resulting the following overall initial results. The most promizing were the: (1) Random Forest, (2) Extra Trees, (3) Decision Tree, (4) Light Gradient Boosting Machine [11].

Classifier	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Extra Trees Classifier	**0.699941**	**0.697118**	**0.699941**	**0.679721**
Random Forest Classifier	**0.697592**	**0.693373**	**0.697592**	**0.676143**
Quadratic Discriminant Analysis	0.459190	0.221843	0.459190	0.299158
K Nearest Neighbors Classifier	0.682032	0.667897	0.682032	0.656546
Decision Tree Classifier	**0.697005**	**0.694699**	**0.697005**	**0.676126**
Gradient Boosting Classifier	0.688784	0.681584	0.688784	0.663057
Logistic Regression	0.468878	0.261091	0.468878	0.304289
AdaBoost Classifier	0.483265	0.294791	0.483265	0.356398
Linear Discriminant Analysis	0.465942	0.260414	0.465942	0.303054
Ridge Classifier	0.474750	0.225388	0.474750	0.305663
Light Gradient Boosting Machine	0.687317	0.677241	0.687317	0.663735
SVM - Linear Kernel	0.474750	0.225388	0.474750	0.305663
Naive Bayes	0.459190	0.221843	0.459190	0.299158

Table 3: Experiments results with classifier comparisons

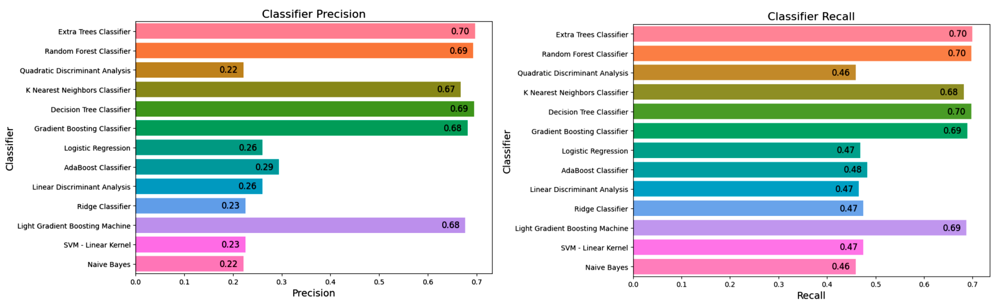

Figure 3: Classifier Precision (left), Classifier Recall (right)

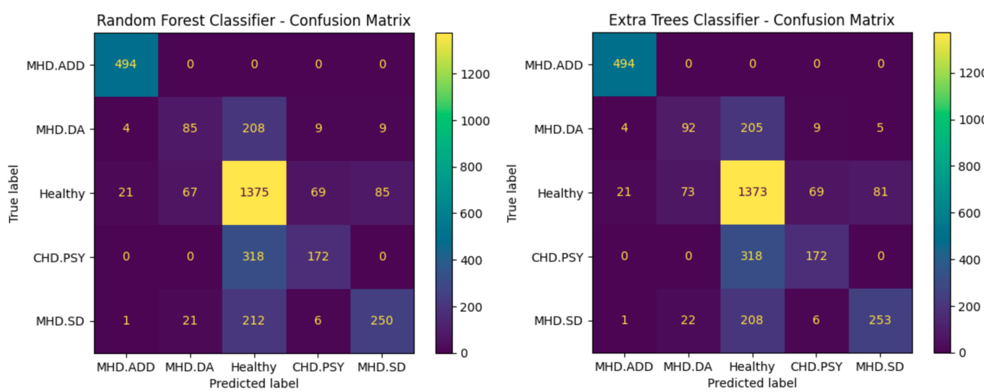

Figure 4: Confusion Matrix - Random Forest (left), Extra Trees (right)

7 Results

The utilization of AI for parsing text (using label distribution as is presented in Table 5.5.1) and sentiment analysis has yielded promising results in the realm of precognition of mental health and neurodegenerative disorders. Studies leveraging these technologies have demonstrated AI's capability to identify linguistic patterns (see Table 5.5.1 for text length distribution) that correlate with symptomatic manifestations of various conditions. The research has shown that individuals with depression tend to exhibit a higher frequency of negative affect words and self-referential pronouns in their communication, which AI algorithms can detect with notable accuracy (see Figure 7 and Figure 8).

In the domain of neurodegenerative diseases, preliminary findings suggest that changes in language complexity, such as simplified syntax and dimin-

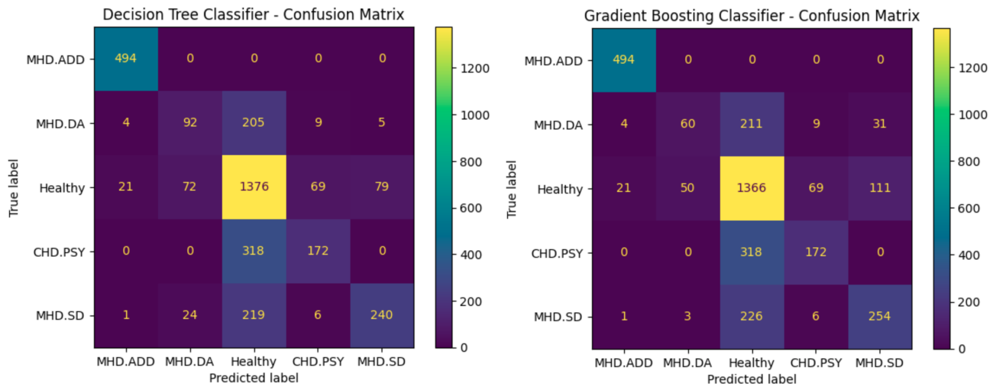

Figure 5: Confusion Matrix - Decision Tree (left), Gradient Boosting (right)

ished vocabulary diversity (Table 7 and (see Table 7), may be quantifiable through AI analysis before these symptoms are clinically evident. This can be particularly observed in conditions like Alzheimer's disease, where progressive cognitive decline has a direct impact on language function. Furthermore, sentiment analysis monitors fluctuations in mood and affect, which are integral to mental health assessment, providing a supplemental, non-invasive tool for tracking patient well-being.

The paper facilitates the monitoring of individuals' communication over time, enabling the identification of trends that may indicate the onset or progression of a disorder. This approach offers a continuous, objective assessment that can complement intermittent clinical evaluations. Moreover, it holds the potential for remote monitoring, which is invaluable for patient populations that may have limited access to regular healthcare services (see Figure 9).

However, these advancements come with the caveat that such technologies are adjuncts and not replacements for traditional diagnostic methods. AI-based predictions require validation through clinical expertise and should be viewed within the broader context of comprehensive medical assessment. The ethical implications of using personal communication data for health monitoring are also under scrutiny, necessitating transparent data handling and stringent privacy safeguards.

The presented methods are emerging as significant contributors to the early detection and monitoring of mental health and neurodegenerative disorders, offering a novel lens through which to understand and manage these complex conditions. The continued refinement of these tools, alongside advances in

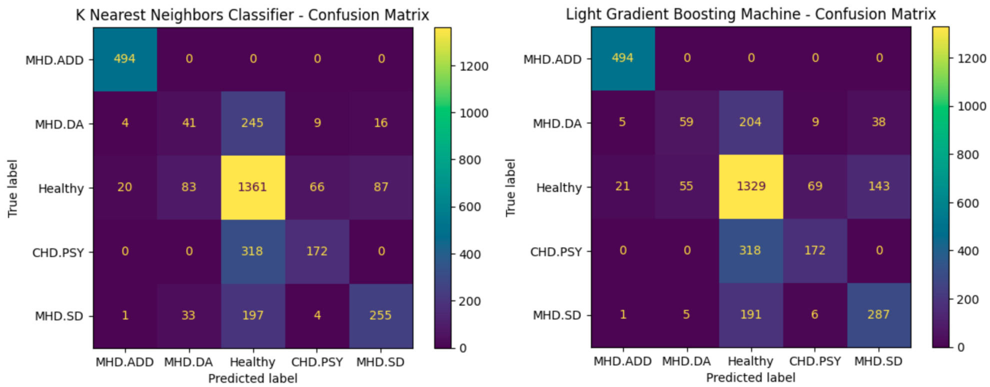

Figure 6: Confusion Matrix - K Nearest Neighbors (left), Light Gradient Boosting Machine (right)

No.	ID	Feature	Importance
1	3254	plotting	**0.051509**
2	5000	sentiment	0.045933
3	4747	voices	0.044404
4	3164	people	0.037201
5	1994	hear	0.034005
6	2610	lost	0.032294
7	3520	real	0.028020
8	3231	places	0.027559
9	3606	remember	0.025091
10	1039	dates	0.024884

Table 4: Top 10 features with Importance levels

machine learning and NLP (see Table 7), promises to enhance the capabilities of medical professionals and improve outcomes for patients.

8 Discussion

The incorporation of AI-based text and sentiment analysis into the diagnostic milieu of mental health and neurodegenerative disorders heralds a novel frontier in early detection and monitoring. This computational approach can transcend conventional constraints by analyzing linguistic and paralinguistic elements in patients' speech or written text, potentially unveiling subtle devi-

Rank	Alzheimer's & Dementia		Depression & Anxiety		None		Psychosis		Suicide & Depression	
No.	**ID**	**IMP**	**ID**	**IMP**	**ID**	**IMP**	**ID**	**IMP**	**ID**	**IMP**
1	familiar	**5.775062**	anxious	**6.343930**	morning	**1.450505**	hear	**8.617279**	suicide	**5.172760**
2	places	5.702947	restless	5.998787	coffee	1.445807	plotting	8.378585	help	4.807741
3	remember	5.150686	worried	5.552964	buy	1.287901	arena	5.983609	kill	4.515317
4	lost	5.135937	nervous	4.982023	cool	1.249352	people	4.887970	life	4.319223
5	hard	4.962242	worry	4.118800	holiday	1.237574	voices	4.455395	just	4.166109
6	dates	4.882358	sleep	2.832804	tweet	1.230690	things	3.417450	wish	4.115592

ID = feature name, IMP - feature importance

Table 5: Top six features with Importance levels per labels

Disease	Precision	Recall	F1-Score	Support
Alzheimer's Disease and Dementia	**0.95**	**1.00**	**0.97**	494
Depression and Anxiety	0.49	0.29	0.37	315
None	0.65	0.85	0.74	1617
Psychosis	0.67	0.35	0.46	490
Suicide and Depression	0.75	0.52	0.61	490
accuracy			0.70	3406
macro avg	0.70	0.60	0.63	3406
weighted avg	0.70	0.70	0.68	3406

Table 6: Extra Trees Classifier Classification Report

Disease	Precision	Recall	F1-Score	Support
Alzheimer's Disease and Dementia	**0.95**	**1.00**	**0.97**	494
Depression and Anxiety	0.49	0.27	0.35	315
None	0.65	0.85	0.74	1617
Psychosis	0.67	0.35	0.46	490
Suicide and Depression	0.73	0.51	0.60	490
accuracy			0.70	3406
macro avg	0.70	0.60	0.62	3406
weighted avg	0.69	0.70	0.68	3406

Table 7: Random Forest Classifier Classification Report

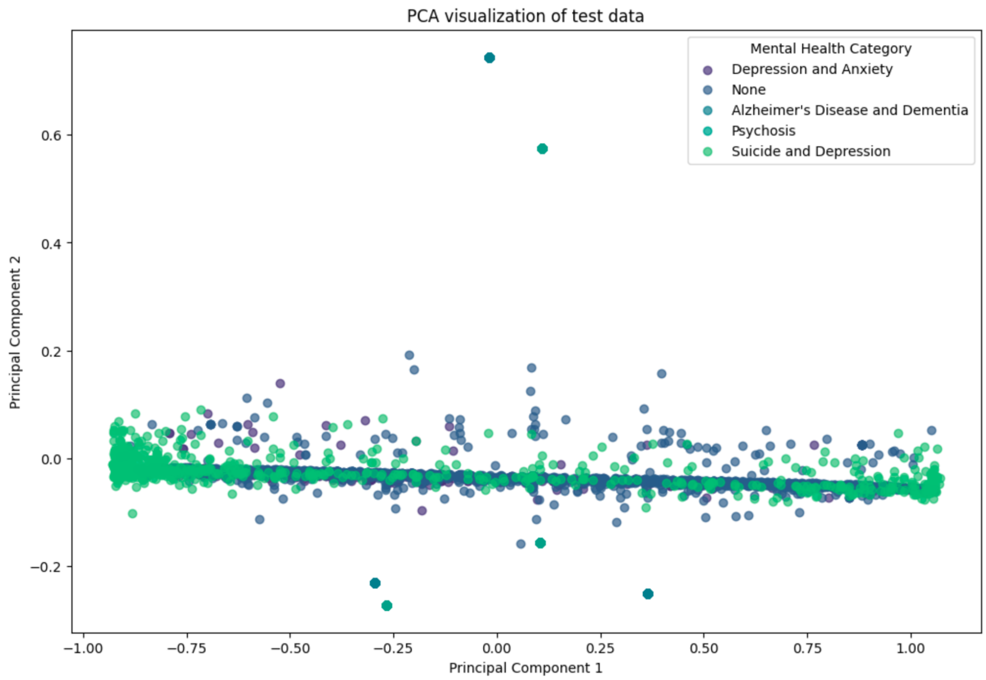

Figure 7: PCA visualization of test data

ations from normative communication patterns indicative of cognitive decline or emotional distress.

The ***Extra Trees Classifier*** (see Table 7) reveals insights into the model's performance across various classes, which in this case are different mental health conditions. The report includes precision, recall, f1-score, and support for each class, as well as overall accuracy and averages. (1) *Alzheimer's Disease and Dementia*: the model demonstrates high precision (0.95) and perfect recall (1.00) in identifying Alzheimer's Disease and Dementia, leading to an excellent f1-score of 0.97. This suggests that the classifier is highly effective in identifying this condition, with a low rate of false negatives and false positives; (2) *Depression and Anxiety*: the performance significantly drops in this category, with a precision of 0.49 and a recall of 0.29, resulting in a f1-score of 0.37. This indicates challenges in accurately classifying cases of Depression and Anxiety, with a higher likelihood of both false positives and false negatives; (3) *None (Healthy)*: the model performs reasonably well in identifying healthy subjects, with a precision of 0.65 and a higher recall of 0.85, culminating in

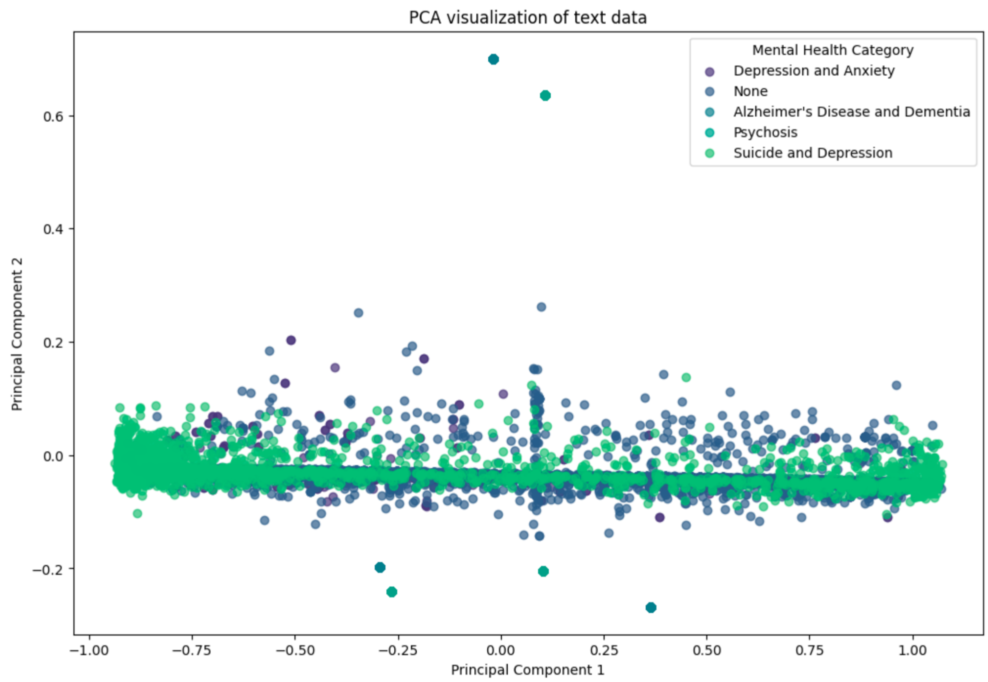

Figure 8: PCA visualization of text data

a f1-score of 0.74. This suggests that while the model can reliably identify healthy individuals, there is still room for improvement in reducing false positives; (4) *Psychosis*: for Psychosis, the model shows a moderate precision of 0.67 but a lower recall of 0.35, leading to a f1-score of 0.46. This implies that while the classifier is relatively reliable when it identifies a case as Psychosis (fewer false positives), it misses a significant number of true Psychosis cases (higher false negatives); (5) *Suicide and Depression*: the model shows fairly good precision (0.75) but moderate recall (0.52) in this category, with a resulting f1-score of 0.61. This suggests a better balance between false positives and false negatives, although there is still a notable number of missed cases; (6) *Overall Performance*: the overall accuracy of the model is 0.70, which is satisfactory but indicates potential for improvement. The macro average f1-score (0.63) and weighted average f1-score (0.68) reflect moderate performance across classes, with better accuracy in some (like Alzheimer's Disease and Dementia) and challenges in others (like Depression and Anxiety); In conclusion, the *Extra Trees Classifier* shows varying levels of effectiveness in identifying

Figure 9: t-SNE visualization of text data

different mental health conditions. Its strength lies in identifying *Alzheimer's Disease* and *Dementia* and the general healthy population, while it faces challenges in accurately classifying Depression and Anxiety, Psychosis, and Suicide and Depression. This variance suggests the need for further model tuning or exploration of alternative features that could improve classification accuracy, especially for the underperforming categories. Additionally, the imbalanced performance across classes indicates the potential benefit of employing techniques to handle class imbalances effectively.

The ***Random Forest Classifier*** (see Table 7) provides a detailed view of the model's performance across different categories related to mental health disorders. This analysis focuses on precision, recall, f1-score for each category, and overall accuracy. (1) *Alzheimer's Disease and Dementia*: the Random Forest Classifier demonstrates excellent performance in identifying Alzheimer's Disease and Dementia, evidenced by high precision (0.95) and perfect recall (1.00), culminating in an f1-score of 0.97. This indicates a strong ability of the model to correctly classify cases of Alzheimer's Disease and Dementia with minimal false positives and negatives; (2) *Depression and Anxiety*: the

Disease	**Precision**	**Recall**	**F1-Score**	**Support**
Alzheimer's Disease and Dementia	**0.95**	**1.00**	**0.97**	494
Depression and Anxiety	0.49	0.29	0.37	315
None	0.65	0.85	0.74	1617
Psychosis	0.67	0.35	0.46	490
Suicide and Depression	0.74	0.49	0.59	490
accuracy			0.70	3406
macro avg	0.70	0.60	0.63	3406
weighted avg	0.69	0.70	0.68	3406

Table 8: Decision Tree Classifier Classification Report

model shows reduced effectiveness in this category with a precision of 0.49 and a lower recall of 0.27, leading to an f1-score of 0.35. This suggests a significant challenge in correctly identifying cases of Depression and Anxiety, as indicated by a considerable number of false negatives and a moderate rate of false positives; (3) *None (Healthy)*: in classifying healthy individuals, the model exhibits decent performance with a precision of 0.65 and a higher recall of 0.85, resulting in a f1-score of 0.74. This indicates a relatively reliable identification of healthy cases, albeit with some room for reducing false positive rates; (4) *Psychosis*: for the category of Psychosis, the model displays a moderate precision of 0.67 but a lower recall of 0.35, yielding an f1-score of 0.46. This points to a reasonable accuracy when the model predicts Psychosis (lower false positives) but a substantial number of missed true cases (higher false negatives); (5) *Suicide and Depression*: the model achieves a fairly good precision of 0.73 and a moderate recall of 0.51, resulting in an f1-score of 0.60. This suggests a somewhat balanced performance in terms of false positives and false negatives, though with room for improvement in recall; (6) *Overall Performance*: the overall accuracy of the model stands at 0.70, reflecting a competent level of performance across all categories. However, the macro average f1-score (0.62) and weighted average f1-score (0.68) indicate a disparity in performance across different categories, with strengths in certain areas like Alzheimer's Disease and Dementia and weaknesses in others such as Depression and Anxiety. In summary, the Random Forest Classifier demonstrates a robust capability in identifying Alzheimer's Disease and Dementia and reasonably good performance in distinguishing healthy individuals. However, it faces challenges in accurately classifying conditions like Depression and Anxiety, Psychosis, and Suicide and Depression. These variations in performance highlight the need for further model refinement or exploration of additional or alternative features, particularly for the categories where performance is lacking. The disparity in classification effectiveness across different mental health conditions also suggests the potential utility of more tailored approaches or models for specific conditions, as well as the importance of considering class imbalance in the training data.

The ***Decision Tree Classifier*** (see Table 7) elucidates its performance in diagnosing various mental health conditions. The report details the model's precision, recall, f1-score for each category, and overall accuracy, offering a comprehensive assessment of its predictive capabilities. (1) *Alzheimer's Disease and Dementia*: in this category, the Decision Tree Classifier exhibits exemplary performance, as evidenced by its high precision (0.95) and perfect recall (1.00), leading to an impressive f1-score of 0.97. This indicates the model's robust ability to accurately identify cases of Alzheimer's Disease and Dementia with minimal error; (2) *Depression and Anxiety*: the model shows limited effectiveness in classifying Depression and Anxiety, with a precision of 0.49 and a recall of 0.29, resulting in an f1-score of 0.37. This suggests considerable challenges in accurately detecting cases of Depression and Anxiety, as indicated by a high rate of false negatives and a significant number of false positives; (3) *None (Healthy)*: the classifier demonstrates reasonable performance in identifying healthy individuals, with a precision of 0.65 and a higher recall of 0.85, yielding an f1-score of 0.74. This suggests a reliable identification of healthy cases, though there is scope for improvement in precision; (4) *Psychosis*: in the Psychosis category, the model achieves moderate precision (0.67) but a lower recall (0.35), resulting in an f1-score of 0.46. This points to a moderate level of accuracy in predicting Psychosis (fewer false positives), but with a notable number of missed true cases (higher false negatives); (5) *Suicide and Depression*: the classifier shows fairly good precision (0.74) but moderate recall (0.49), culminating in an f1-score of 0.59. This balance suggests a better equilibrium between false positives and false negatives, although the number of missed cases is still significant; (6) *Overall Performance*: the Decision Tree Classifier achieves an overall accuracy of 0.70, indicating a satisfactory level of performance across all classes. However, the macro average f1-score (0.63) and weighted average f1-score (0.68) highlight disparities in performance across different categories, with significant effectiveness in some areas (such as Alzheimer's Disease and Dementia) and limitations in others (notably Depression and Anxiety); In conclusion, the Decision Tree Classifier shows a strong capacity to accurately identify Alzheimer's Disease and Dementia and reasonably good ability to distinguish healthy individuals. However, it faces considerable challenges in effectively classifying conditions like Depression and Anxiety, Psychosis, and Suicide and Depression. These variances underscore the need for further refinement of the model or exploration of more sophisticated or specialized features to enhance its predictive accuracy, particularly in the underperforming categories. The observed disparities also suggest the necessity of adopting strategies to address potential class imbalances in the training process to improve the model's diagnostic capabilities across a broader spectrum of mental health conditions.

Moreover, AI-driven methodologies can harness large datasets to identify linguistic biomarkers that may be imperceptible to human clinicians, thereby augmenting the sensitivity of early screening efforts. This innovation also promises to democratize mental health diagnostics by enabling remote and scalable tools that can reach underserved populations, circumventing barriers such as stigma and geographical isolation. In the domain of neurodegenerative disorders, text analysis might track longitudinal changes in language usage over time, facilitating a more dynamic understanding of disease progression. Collectively, these advances stand to refine diagnostic accuracy, enhance patient engagement in their mental wellness, and tailor interventions to the linguistic and emotional profiles discerned through AI analysis.

9 Limitations of AI-parsed text analysis on prediagnosis

The precognition of mental health and neurodegenerative disorders through AI-parsed text and sentiment analysis, while innovative, encounters specific constraints that limit its current clinical utility. One significant limitation is the potential for algorithmic bias, where AI models may exhibit skewed performance due to imbalances or lack of diversity in training datasets. Such biases can result in differential accuracy across populations, leading to misclassification or underrepresentation of certain demographic groups.

Moreover, the complexity of human language, replete with sarcasm, metaphor, and cultural idioms, presents a formidable challenge for AI interpretation [2]. Sentiment analysis algorithms may misclassify the emotional valence of such nuanced communication, potentially yielding false indicators of a disorder. The inherent ambiguity in language, especially when considering text out of context or in short snippets typical of digital communication, further exacerbates the risk of erroneous conclusions.

Data privacy is a critical issue, as the use of personal text data for AI analysis [10] necessitates rigorous consent protocols and data protection measures to safeguard against breaches of confidentiality. Ethical considerations also extend to the implications of false positives or negatives, which can have profound effects on individuals' lives, including unwarranted distress, stigmatization, or inappropriate medical intervention.

The variability in individual communication styles and changes over time adds to the complexity of establishing consistent and reliable diagnostic criteria through text analysis. For neurodegenerative diseases, which progress over time, establishing a baseline for comparison can be challenging, and deviations from the baseline may be subtle and gradual, making them difficult to detect reliably.

Lastly, the current diagnostic standards for mental health and neurodegenerative disorders involve a multifaceted clinical approach, including direct patient interviews, cognitive assessments, and medical examinations. AI-parsed text and sentiment analysis, while providing valuable supplementary information, cannot yet replicate the depth and breadth of these traditional methods. Clinicians must interpret AI-generated data with caution, integrating it with a comprehensive clinical picture to make informed decisions regarding diagnosis and treatment.

10 Future development

Our objective is to conduct a comprehensive investigation using a validated dataset, while also enhancing the model by incorporating speech analysis within a high-performance computing (HPC) environment [81]. The present stage of the investigation encounters constraints within the Google Colab Pro platform.

The future development lines of AI will offer more sensitive, specific, and timely identification of mental health and neurodegenerative disorders, ultimately leading to better patient outcomes through early and personalized care. The trajectory of AI in the precognition of mental health and neurodegenerative disorders is trending towards several specific lines of development:

1. **Voice analysis expansion** [19]: The tonal quality, pitch fluctuations, speech rate, and pause patterns in voice data can be quantitatively analyzed to detect early subtle signs of cognitive decline or emotional distress. For example, monotone speech may be an early indicator of Parkinson's disease, while a decrease in speaking rate and increased pause time

may suggest Alzheimer's disease. Future AI models could be trained to detect these vocal biomarkers with greater precision, utilizing deep learning techniques to learn from a vast array of voice samples;

2. **Contextual and idiomatic language understanding** [24]: Developing AI systems with an enhanced understanding of context will involve creating more sophisticated NLP algorithms capable of detecting sarcasm, irony, and humor. This requires training on diverse datasets that include various dialects and colloquialisms to reflect the true range of human language use;

3. **Neuroimaging integration** [48]: Combining AI-parsed text and sentiment analysis with data from neuroimaging techniques like fMRI or PET scans could lead to more accurate identifiers of disease. AI could help correlate changes in speech and writing with specific neural patterns associated with neurodegeneration;

4. **Genomic correlations** [22]: AI could be used to find associations between linguistic changes and genetic markers. By analyzing the genetic profiles of individuals alongside language symptoms, researchers can identify hereditary patterns in neurodegenerative disease manifestation;

5. **Real-time wearable monitoring** [10]: The future may see the proliferation of wearable devices that not only track physical health metrics but also capture speech and writing in real-time. AI systems could analyze this data continuously to identify trends predictive of mental health and cognitive conditions;

6. **Digital phenotyping** [56]: This involves the collection and analysis of data on behavior and lifestyle as manifested in the digital realm, from typing speeds on smartphones to interaction patterns on social media. Such phenotyping could provide additional clues to cognitive and mental health status;

7. **Ethical data governance**: As AI systems gain access to more sensitive personal data, the development of rigorous ethical frameworks to govern data use will be crucial. This includes transparent AI operations, user consent protocols, and privacy-preserving analytics techniques such as federated learning;

8. **AI education**: Efforts will be made to increase the explainability of AI models in healthcare, enabling clinicians to understand and trust AI-

driven assessments. Explainable AI will be essential for integrating AI insights into clinical decision-making.

Each of these development lines aims to *enhance* the *precision*, *reliability*, and *ethical integrity of AI applications* in mental health and neurodegenerative disease care, promising a future of proactive and personalized healthcare solutions for performance sports platforms and sports safety solutions [83].

11 Conclusions

The integration of AI in parsing textual data and performing sentiment analysis has been progressively recognized as a substantial adjunct in the field of mental health (such as depression, anxiety, psychotic disorders, Alzheimer's disease and dementia) and neurodegenerative disorders (like Parkinson's disease). Empirical research has underscored AI's potential in flagging early symptomatology and in monitoring the progression of such conditions through the analysis of linguistic cues. Individuals exhibiting mental health disorders, for instance, have been found to demonstrate distinctive patterns in language and sentiment that AI algorithms can discern, often with considerable accuracy. These patterns include a prevalence of negatively connotated language and a proclivity for certain grammatical structures, indicative of affective disturbances or cognitive decline.

For neurodegenerative disorders, shifts in linguistic ability, such as a waning in vocabulary richness and sentence complexity, may serve as early indicators detectable by AI before traditional diagnostic methods yield definitive results. Sentiment analysis has augmented this detection capacity by providing a continuous measure of emotional states, thus facilitating a dynamic assessment framework that aligns closely with the episodic and fluctuating nature of these disorders.

However, the translation of these analytical advancements into clinical practice entails navigating the challenges associated with data diversity, representativeness, and privacy. The applications of AI in this context also raise ethical questions pertaining to the handling of sensitive personal data and the implications of predictive analytics on patient autonomy and stigma. Furthermore, the current outcomes from AI analytics in this sphere are predominantly correlative rather than causative, necessitating cautious interpretation and integration with clinical expertise.

In conclusion, while AI-parsed text and sentiment analysis represent burgeoning fields with transformative potential for precognitive assessments, they are complemented by an array of limitations that require careful management. Future development in this domain is contingent upon methodological enhancements, multidisciplinary collaborations, and the establishment of rigorous ethical and operational protocols to safeguard against the misapplication of AI and to secure the confidentiality and integrity of patient data.

Overall, while AI-parsed text and sentiment analysis offer promising adjunctive tools for the precognition of certain disorders, they cannot yet replace the nuanced judgment of healthcare professionals. Their role is currently best suited to being one of several streams of data informing a holistic clinical picture. Clinicians must interpret AI-generated data with caution, integrating it with a comprehensive clinical picture to make informed decisions regarding diagnosis and treatment.

The expected outcomes of AI-parsed text and sentiment analysis *in the sports domain* is becoming increasingly vital, particularly for the early recognition of mental health concerns and the precursors to neurodegenerative disorders among athletes. The intense physical demands, psychological stress of competition, and high-impact nature of many sports can precipitate or aggravate conditions such as depression, anxiety, and CTE (Chronic Traumatic Encephalopathy).

Fields of interests are as follows: (1) **Mental health**: AI's ability to analyze linguistic patterns can reveal signs of mental distress that might be overlooked in traditional assessments. For example, a football player's social media posts could be analyzed for changes in emotional tone, indicating stress or depression, which could be related to on-field performance pressure or injury recovery processes. An AI system that notes an increase in language expressing anxiety or negative sentiments could trigger early psychological support interventions; (2) **Neurodegenerative disorder predictions**: In contact sports, repeated head injuries are a known risk factor for neurodegenerative diseases. AI can monitor athletes' speech and writing for coherence, word-finding difficulties, and other linguistic impairments over time. This longitudinal analysis could indicate early cognitive changes suggestive of conditions like CTE well before clinical symptoms manifest, enabling preemptive health measures and informing decisions on career longevity; (3) **Concussion management**: AI can play a pivotal role in post-concussion care. Athletes' communication before and after head injuries can be scrutinized for changes in language processing, which can be subtle and not immediately apparent. Consistent monitoring of an athlete's linguistic expression post-injury can aid in tailoring individualized recovery programs and determining the safest time for return to play; (4) **Performance and well-being correlations**: The sentiment analysis of athlete interviews and press conferences can offer insights into the relationship between an athlete's psychological state and performance. By quantifying sentiment, AI could help teams and coaches understand how emotional factors influence game-day performance, contributing to strategies that optimize athlete well-being and effectiveness; (5) **Cognitive baselines long-term monitoring**: Establishing cognitive and linguistic baselines for athletes and tracking any deviations from these over time can allow for the early detection of potential health issues. AI systems can be employed to perform this tracking unobtrusively, analyzing routine communications without requiring formal clinical testing.

In summary, the integration of the methods presented in this paper into sports safety initiatives offers a more nuanced and proactive approach to monitoring the mental and neurological health of athletes. It provides an additional layer of protection by identifying potential issues early, thereby facilitating timely interventions and contributing to the overall well-being and longevity of sports professionals.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	artificial intelligence
NLP	natural language processing
ML	machine learning
DSM	Diagnostic and Statistical Manual of Mental Disorders
ICD	international Classification of Diseases
CSF	cerebrospinal fluid
MRI	magnetic resonance imaging
PET	positron emission tomography
CT	computed tomography
TF-IDF	term frequency-inverse document frequency
SVM	support vector machine
HPC	High Performance Computing

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