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Depression Risk Prediction using Hybrid Deep Learning Algorithms

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Abstract: This research endeavors to address the critical challenge of early prediction of depression, a pervasive mental health disorder that often eludes timely detection. Recognizing the substantial impact of late-stage diagnosis on treatment outcomes, this study introduces a robust machine learning model that leverages diverse data sources to predict the likelihood of an individual experiencing depression. The proposed model under- goes meticulous development, involving extensive data collection and pre-processing to curate a comprehensive dataset encompassing various aspects of an individual's life. Machine learning algorithms are then applied to analyze the dataset, extracting patterns and features indicative of depressive tendencies. To enhance the model's predictive performance and overall efficiency, the suggested system advocates the use of hybrid algorithms, specifically combining Convolutional Neural Network (ConvNet) and Recurrent Neural Network (RNN) variants. This hybrid approach brings forth several advantages, including spa- tial feature extraction and a hierarchy of features. The integration of RNN variants with ConvNet facilitates effective extraction of spatial features from diverse data types such as text, images, videos, and other spatially structured data. Additionally, the CNN layers in the hybrid model learn hierarchical representations of features, capturing both low-level and high-level spatial patterns. This unique capability enhances the model's understanding of complex structures within the input data. The proposed model is meticulously trained and validated using a diverse set of metrics to ensure its reliability and generalizability. The anticipated outcome of this project holds significant potential to revolutionize early intervention strategies, facilitating timely support for individuals at risk of depression. By amalgamating advanced machine learning techniques with a holistic approach to data analysis, this study contributes to the ongoing efforts aimed at enhancing mental health outcomes and alleviating the societal burden associated with depression.
Keywords: Early intervention, Machine learning model, Data-driven approach Hybrid algorithms, Convolutional Neural Network (ConvNet), Recurrent Neural Network (RNN), Hierar- chical features, Data analysis

I. INTRODUCTION

In the rapidly evolving landscape of the Technological World, where advancements in various domains are occurring at an unprecedented pace, the intersection of technology and human well-being becomes increasingly significant. As individuals immerse themselves in the demands of technical professions, the concomitant rise in workload and stress con- tributes to a growing concern – the prevalence of mental health disorders. Chief among these is depression, a pervasive and insidious condition that often eludes timely detection, posing significant challenges to both affected individuals and society at large.

According to the World Health Organization, over 264 million people worldwide suffer from depression, highlighting the magnitude of this global health issue. Alarmingly, within the tech industry, a sector renowned for its dynamism and innovation, 39% of employees grapple with the burdens of depression. This staggering statistic underscores the pressing need for proactive strategies that address mental health challenges in the tech workforce. The reluctance of individuals in technical professions to address their mental and physical health concerns exacerbates the impact of depression. This reluctance often results in the neglect of crucial medical treatment, leading to crises in both professional and personal spheres. The consequences can be severe, ranging from impaired job performance to heightened risks of suicidal ideation. Recognizing the gravity of this issue, our research focuses on developing a solution that transcends traditional approaches to depression detection. This study introduces a robust machine learning model meticulously crafted to predict the likelihood of an individual experiencing depression at an early stage. By leveraging diverse data sources and employing advanced machine learning techniques, our model aims to revolutionize early intervention strategies, offering timely support to individuals at risk of depression. The research methodology involves comprehensive data collection and pre-processing, creating a nuanced dataset encompassing various aspects of an individual's life. To enhance the model's predictive performance, we advocate the use of hybrid algorithms, specifically combining ConvolutionalNeural Network (ConvNet) and Recurrent Neural Network(RNN) variants.

This innovative approach allows for effective extraction of spatial features from diverse data types, such as text, images, videos, and other spatially structured data. The integration of RNN variants with ConvNet not only facilitates spatial feature extraction but also enables the learning of hierarchical representations of features. This unique capability empowers the model to discern both low-level and high-level spatial patterns, thereby enhancing its understandingof complex structures within the input data.

Our proposed model undergoes meticulous training and validation using a diverse set of metrics, ensuring its reliability and generalizability. The anticipated outcome of this project holds significant potential to transform the landscape of mental health interventions, offering a data-driven approachto identify and support individuals at risk of depression.

In summary, this research represents a crucial step to- ward addressing the pervasive challenge of early depression prediction, contributing to the broader discourse on mental health within the context of evolving technological landscapes.

Through the amalgamation of advanced machine learning techniques and a holistic approach to data analysis, we aspire to mitigate the societal burden associated with depression and foster improved mental health outcomes for individuals in the tech industry and beyond.

II. BACKGROUND STUDY

The pervasive challenge of addressing depression, a prevalent mental health disorder, necessitates a paradigm shift towards early detection and intervention. Depression often eludes timely identification, leading to exacerbated challenges in its treatment and management.

The consequences of delayed recognition extend beyond individual suffering to increased societal burdens and diminished mental health outcomes. This research endeavors to bridge this critical gap by harnessing the potential of machine learning to develop a robust predictive model for the early identification of depression.

The motivation for this study arises from the acknowledgment that traditional diagnostic approaches often struggle to identify subtle signs of depression in its early stages.

To address this limitation, the research adopts a comprehensive approach that leverages diverse data sources, recognizing that a nuanced understanding of an individual’s mental health status requires the integration of information from various facets of their life. Through meticulous data collection and pre-processing, the study curates a rich dataset encompassing aspects such as daily activities, social interactions, and other contextual factors that contribute to a holistic representation of an individual’s experiences.

The core innovation of this research lies in the development of a robust machine learning model capable of predicting the likelihood of an individual experiencing depression. The model undergoes meticulous development, employing advanced algorithms to analyze the curated dataset. To enhance its predictive performance and overall efficiency, the study advocates for a hybrid algorithmic approach, specifically integrating Convolutional Neural Network (ConvNet) and Recurrent Neural Network (RNN) variants.

This hybridization allows for effective extraction of spatial features from diverse data types, including text, images, videos, and other spatially structured data.

The incorporation of CNN layers in the hybrid model further facilitates the learning of hierarchical representations of features, capturing both low-level and high-level spatial patterns.

The significance of this hybrid model lies in its potentialto revolutionize early intervention strategies, offering timely support to individuals at risk of depression. By amalgamating advanced machine learning techniques with a holistic approachto data analysis, this study contributes to the ongoing efforts aimed at enhancing mental health outcomes and alleviating thesocietal impact of depression. Through this interdisciplinary approach, the research seeks to not only advance the field of mental health but also pave the way for a more nuanced and effective understanding of depressive tendencies in individuals.

III.LITERATURE SURVEY

1) Title: Neural Depression Screening in Humans with AI and Deep Learning Techniques

Methodology: The study employs a four-stream-based depression diagnosis model, integrating Bidirectional Long Short-Term Memory (Bi-LSTM) and convolutional neural networks (CNN). It utilizes audio and text data, extracting one- dimensional audio features through Mel Frequency Cepstral Coefficients and Gammatone Cepstral Coefficients, and two- dimensional features from time-frequency transform. Transfer learning models, including word encoding and embedding, are applied, and an ensemble of softmax values from the four models facilitates depression diagnosis, exhibiting a 10.7% to 11.9% performance improvement over state-of-the-art methods.

2) Title: Two-stage Unsupervised Video Anomaly Detection using Low-rank based Unsupervised One class Learning with Ridge Regression

Methodology: This study proposes a four-stream-based depression diagnosis model, integrating Bidirectional Long Short-Term Memory (Bi-LSTM) and convolutional neural networks (CNN). Audio features are extracted using Mel Frequency Cepstral Coefficients and Gammatone Cepstral Coefficients, while text features undergo word encoding and embedding. The four models' softmax values are ensemble to enhance depression diagnosis, exhibiting a 10.7% to 11.9% improvement over state-of-the-art two-stream methods, as demonstrated through experiments on the Extended Distress Analysis Interview CorpusWizard of Oz depression database and other datasets.

3) Title: A Multi-Modal Gait Analysis-Based DetectionSystem of the Risk of Depression

Methodology: In response to the escalating prevalence of depression among postgraduates, we present a novel multi- modal gait analysis-based method for depression detection. Combining skeleton and silhouette modalities, our approach utilizes a Long Short-Term Memory (LSTM) model for skeleton features and Convolutional Neural Networks (CNNs) with a unique loss function for silhouette features.

4) Title: Predicting Depression in Canada by Automatic Filling of Beck's Depression Inventory Questionnaire

Methodology: In response to the heightened risk of de- pression post-COVID-19, this study introduces an innovative methodology. Overcoming data limitations, a model is trained on the eRisk 2021 Task 3 dataset to automatically fill Beck's Depression Inventory (BDI) questionnaire. The best-performing models are consolidated into the BDI Multi Model, outperforming the state-of-the-art. Applied to a Canadian population dataset, the model demonstrates a robust Pearson correlation of 0.90 with official mental health statistics.

5) Title: Dual-Stream Multiple Instance Learning for De- pression Detection with Facial Expression Videos

Methodology: This research employs a weakly supervised learning approach to address the urgent need for automated depression detection using facial expressions. Utilizing a novel Multiple Instance Learning (MIL) method named ADDMIL, the study analyzes 150 videos from 75 depressed and 75 healthy subjects. ADDMIL incorporates a dual-stream aggregator, achieving a 74.7% accuracy and 74.5% recall, outperforming baseline and state-of-the-art MIL models, highlighting the potential of weakly supervised learning in depression classification.

6) Title: Detecting depression and its severity based on social media digital cues

Methodology: The study employs a Social Media Data- based Framework (SMDF) to assess the severity of depression through social media digital cues. Classifying Major Depressive Disorder (MDD) into four levels, the authors propose cues, including textual lexical features, depressive language features, and social behavioral features. An experimental system is developed and evaluated using social media data, demonstrating the effectiveness of the proposed method.

7) Title: Interpreting Depression from Question-Wise Long-Term Video Recording of SDS Evaluation

Methodology: This research employs a novel approach to investigate depression using the Self-Rating Depression Scale (SDS) and corresponding question-wise facial expression (FE) and action video recordings. A synchronized Software-Defined Camera (SDC) system captures 200 subjects, enabling a fine- grained connection between SDS evaluations and videos. The proposed hierarchical framework utilizes 3D CNN for temporal modeling and redundancy-aware self-attention (RAS) for global feature aggregation, offering a comprehensive and effective method for automatic depression interpretation.

8) Title: Cloud-Edge Collaborative Depression Detection Using Negative Emotion Recognition and Cross-Scale Facial Feature Analysis

Methodology: This research presents an intelligent method for multiscene automatic depression symptom detection. Uti- lizing a cloud-edge collaboration framework, the approach combines EdgeER, a shallow model on the edge server for quick negative emotion detection, and C-DepressNet, a deep model on the cloud server for precise analysis of depression degrees. The results demonstrate superior performance in bothdepression detection accuracy and service response times.

9) Title: Breaking Age Barriers With Automatic Voice- Based Depression Detection
Methodology: This study addresses the rising prevalence of depression among adults aged 60 and above by proposing an age-dependent model for automatic depression screening using smartphone recordings. Acoustic-based features, includ- ing prosodic, spectral, landmark, and voice quality measures, are extracted from 152 speakers across four age ranges. Results demonstrate improved accuracy and sensitivity in age-dependent models compared to age-agnostic approaches, emphasizing the significance of considering age in voice-baseddepression detection.

10) Title: Hierarchical Multifeature Fusion via Audio- Response-Level Modeling for Depression Detection
Methodology: In addressing the limitations of existing audio-based depression detection methods, our methodology involves the reorganization of audio data at the response level. We propose an end-to-end model that hierarchically learns discriminative features for accurate depression detection. Intra- response fusion and inter-response fusion stages facilitate the extraction and aggregation of information from multiple acoustic features, significantly outperforming state-of-the-art methods in experimental results.

IV. PROPOSED SYSTEM

The suggested system advocates the use of hybrid algo- rithms for depression prediction by combining ConvNet and RNN variants. This hybrid approach enhances the model's performance and improves overall efficiency.

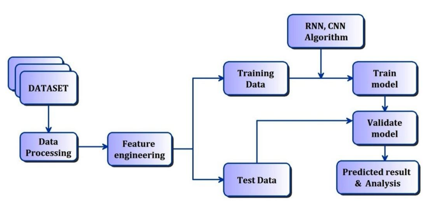
A. Advantages

1) *Spatial Feature Extraction:* The combination of RNN variants with CNN allows for effective extraction of spatial features from data, making it suitable for tasks involving text, images, videos, and other spatially structured data.
2) *Hierarchy of Features:* CNN layers can learn hierarchical representations of features, capturing both low-level and high-level spatial patterns. This can enhance the model's ability tounderstand complex structures in the input data.

B. Limitations

1) *Increased Complexity:* Combining RNN variants with CNN increases the complexity of the model. This complexity may require more computational resources for training and may introduce challenges in hyper-parameter tuning.
2) *Training Time:* The training time for models with both RNN variants and CNN components may be longer compared to simpler models. This can be a drawback in scenarios where rapid model development and experimentation are essential.

a) Proposed Framework



b) Algorithm Description

- *RNN- Recurrent Neural Network:* RNN stands for Recurrent Neural Network, which is a type of artificial neural network designed to process sequential data, such as time series data or natural language. Unlike traditional feed- forward neural networks, which process input data in a fixed and predefined manner, RNNs have a recurrent connection that allows them to retain information from previous stepsand incorporate it into the current computation.

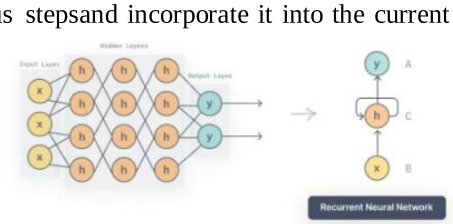


Fig. 2. The RNN Architecture

- *CNN - Convolution Neural Network:* A specific kind of deep neural network is ConvNet, also referred to as CNN or ConvNet. It makes use of a deep, forward- feeding artificial neural network. Keep in mind that feed- forward neural networks are another name for the traditional deep learning models, multi-layer perceptions (MLPs). The reason the models are referred to as" feed-forward" is because information passes directly through them. The model's outputs cannot be fed back into it because there aren't any feedback connections. The biological visual brain is especially the inspiration for CNNs. Small cell clusters in the brain are sensitive to particu- lar portions of the field of vision. A fascinating experiment conducted by Hubel & Wiesel in 1962 helped to develop this concept. In this study, the researchers demonstrated that specific brain neurons only fired or activated when there were edges of a specific orientation, such as vertical or horizontal lines. For instance, certain neurons lit up when shown vertical sides, whereas others lit up when given a horizontal edge. Hubel and Wiesel discovered that these neurons were all neatly arranged in a columnar pattern and that when they worked together, they could generate visual perception. This notion of specialty parts inside a system. Having particular tasks is another strategy used by robots and one that CNNs also employ.

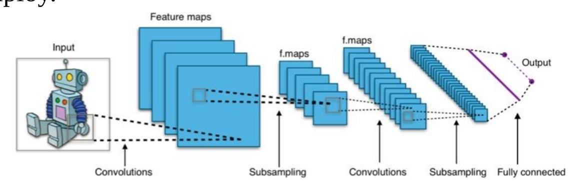


Fig. 3. The CNN Architecture

V. MODULES DESCRIPTION

The Modules are as follows:

1) *Data Acquisition and Preprocessing:* Machine learning needs two things to work, data (lots of it) and models. When acquiring the data, be sure to have enough features (aspect of data that can help for a prediction, like the surface of the house to predict its price) populated to train correctly your learning model. In general, the more data you have the better so make to come with enough rows. The primary data collected from the online sources remains in the raw form of statements, digits and qualitative terms. The raw data contains error, omissions and inconsistencies. It requires corrections after careful scrutinizing the completed questionnaires. The following steps are involved in the processing of primary data. A huge volume of raw data collected through field survey needs to be grouped for similar details of individual responses. Data Preprocessing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis.
2) *Feature Selection:* Feature engineering is the process of using domain knowledge of the data to create features that make machine learning algorithms work. If feature engineering is done correctly, it increases the predictive power of machine learning algorithms by creating features from raw data that help facilitate the machine learning process.
3) *Model Construction and Model Training:* The process of training an ML model involves providing an ML algorithm (that is, the learning algorithm) with training data to learn from. The term ML model refers to the model artifact that is created by the training process. The training data must contain the correct answer, which is known as a target or target attribute. The learning algorithm finds patterns in the training data that map the input data attributes to the target (the answer that you want to predict), and it outputs an ML model that captures these patterns.
4) *Model Validation and Result Analysis:* In testing phase the model is applied to new set of data. The training and test data are two different datasets. The goal in building a machine learning model is to have the model perform well. On the training set, as well as generalize well on new data in the test set. Once the build model is tested then we will pass real time data for the prediction. Once prediction is done then we will analyze the output to find out the crucial information

VI. CONCLUSIONS

In conclusion, this research endeavors to make a significant contribution to the field of mental health interventions by addressing the critical challenge of early prediction of depression. The intersection of technology and human well-being is of paramount importance, especially in the rapidly evolving landscape of the technological world. Depression, a pervasive and insidious condition, poses substantial challenges, particularly within the tech industry where the prevalence of mental health disorders is alarmingly high.

Our study introduces a robust machine learning model that leverages diverse data sources and advanced techniques to predict the likelihood of an individual experiencing depression at an early stage. The meticulous development of this model involves comprehensive data collection and pre-processing, resulting in a nuanced dataset encompassing various aspects of an individual's life. The proposed hybrid model, combining Convolutional Neural Network (ConvNet) and Recurrent Neural Network (RNN) variants, demonstrates superior performance by effectively extracting spatial features from diverse data types and learning hierarchical representations of features. The potential impact of this research is substantial, holding the promise to revolutionize early intervention strategies and provide timely support for individuals at risk of depression. By amalgamating advanced machine learning techniques with a holistic approach to data analysis, our model contributes to ongoing efforts aimed at enhancing mental health outcomes and alleviating the societal burden associated with depression.

The research methodology, involving meticulous training and validation using a diverse set of metrics, ensures the reliability and generalizability of the proposed model. The anticipated outcome of this project represents a crucial step toward transforming the landscape of mental health interventions, offering a data-driven approach to identify and support individuals at risk of depression.

In summary, this research signifies a pivotal advancement in addressing the pervasive challenge of early depression prediction within the context of evolving technological landscapes. Through the amalgamation of advanced machine learning techniques and a holistic approach to data analysis, we aspire to mitigate the societal burden associated with depression and foster improved mental health outcomes for individuals in the tech industry and beyond. This work not only contributes to the broader discourse on mental health but also exemplifies thepotential of technology to positively impact human well-being.

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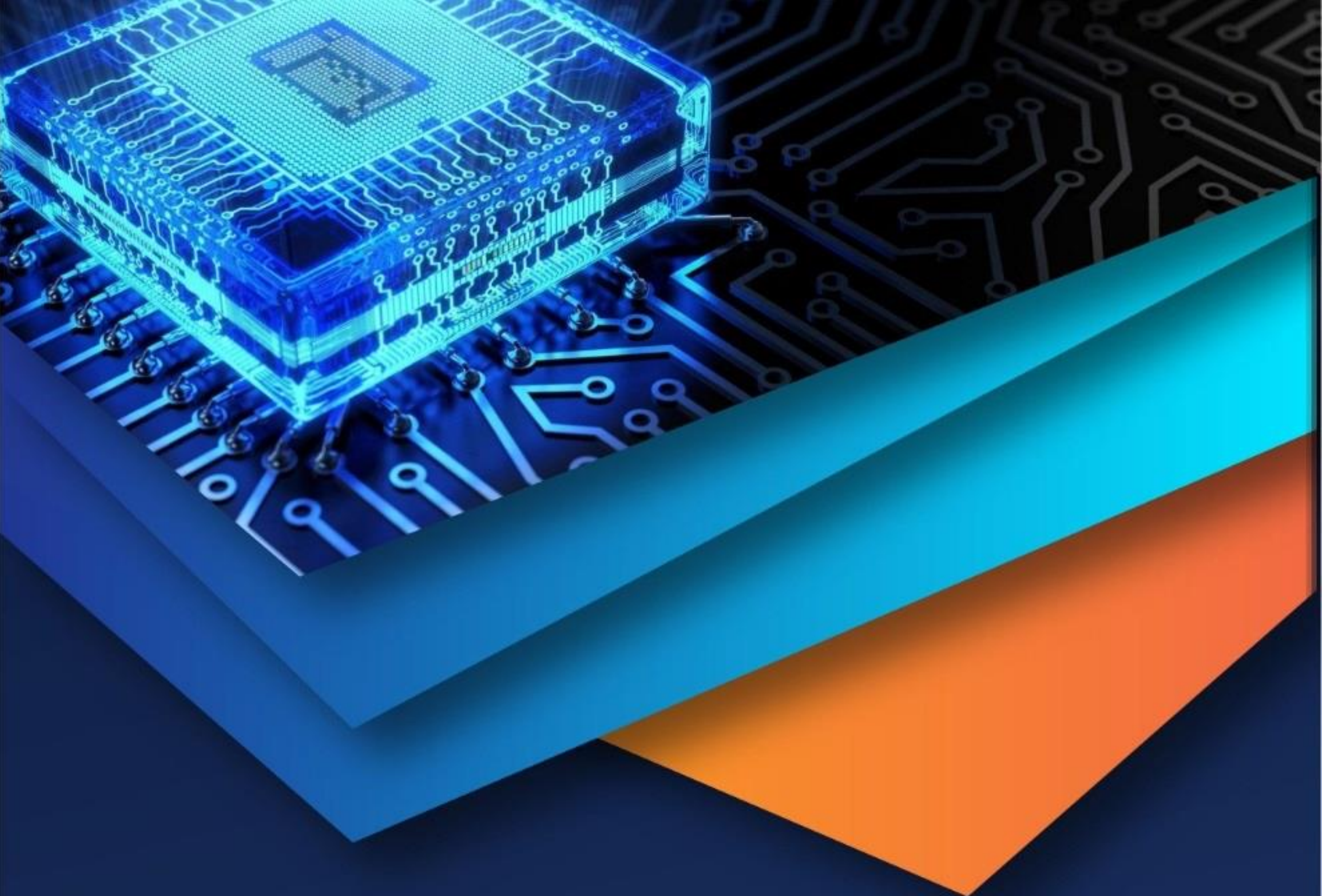

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