AN EMPIRICAL MACHINE-LEARNING MODEL FOR IMPROVING MENTAL ILLNESS DISORDER PREDICTION ACCURACY WITH HYBRID MACHINE LEARNING MODELS

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ABSTRACT

Mental illness disrupts a person's entire world, impacting how they think, feel, and behave. It can trigger negative emotions like depression and anxiety, or lead to risky behaviours like substance abuse or social withdrawal. This can create a ripple effect, making it harder to concentrate at work or school, straining relationships with loved ones, and even impacting physical health. With professional help, people with mental illness can learn to manage their condition, improve their overall well-being, and find success in various aspects of life. This study proposed a hybrid model performed accuracy more than 93% applied on dataset having 1259 records and 26 features. This proposed model performed best to investigates the feature importance from the datasets to infer the significant importance of social support, learning environment. It looks at the performance of different ML models on a survey-based dataset, inferring a significant classification performance by a hybrid algorithm.

KEYWORDS: Mental illness disorder, Machine learning, hybrid approach, Feature importance.

1. INTRODUCTION

Far from being just a mind game, mental illness disorders disrupt the very core of who we are. They distort our perception of reality, turning our feelings into a depressive or anxious rollercoaster and our thoughts into negative spirals. These internal changes can have an external manifestation, driving us to engage in risky activities or isolate ourselves from others. It becomes difficult to concentrate at work, uphold relationships, and even manage our physical health because of this cascading effect. The good news is that mental illness need not be a lifelong stigma. With the right assistance, we may learn how to control these illnesses, regain mental stability, meet life's obstacles head-on, and, in the end, lead happy, meaningful lives even in the face of these circumstances. Mental illness disorders, though disruptive, are not life sentences. By seeking professional help, we can embark on a journey of self-discovery, learning to manage these conditions. This path leads towards rebuilding emotional stability, reclaiming focus, and ultimately, living fulfilling lives, even with these disorders as companions.

1.1 SOME COMMON TYPES OF MENTAL ILLNESS DISORDER

A wide spectrum of problems that affect a person's cognitive, emotional, and behavioural well-being are referred to as mental health disorders. Anxiety disorders, such as panic disorder and generalised anxiety disorder, show up as abrupt, severe episodes of terror or ongoing worry, respectively. Emotional states are disrupted in mood disorders, like Major Depressive Disorder and Bipolar Disorder. Mood states can range from constant melancholy to oscillations between manic episodes and depression. The symptoms of schizophrenia, a severe psychotic illness, include hallucinations, altered thinking, and diminished functioning. Anorexia nervosa and bulimia nervosa are two eating disorders that are indicative of dysfunctional connections with food and body image. Persistent patterns of behaviour, thought, and interpersonal functioning are characteristics of personality disorders, such as Narcissistic and Borderline Personality Disorders. Repetitive actions and intrusive thoughts are symptoms of obsessive-compulsive disorder. After experiencing trauma, one may acquire post-traumatic stress disorder, which can cause upsetting symptoms. Impulsivity, hyperactivity, and chronic inattention are symptoms of attention-deficit/hyperactivity disorder. Communication and social skills are challenged by autism spectrum disorder. For a proper diagnosis and successful treatment, which frequently includes psychotherapy, medication, and supportive treatments customised to the individual disorder—seeking professional assistance is essential.

1.2 ROLE OF MACHINE LEARNING

Machine learning leaps into the fight against mental illness by analysing vast amounts of data. Social media posts, medical records, and even brain scans can be sifted for patterns that might signal an emerging mental health issue. These algorithms cannot diagnose, but by spotting early warning signs, they can nudge individuals towards getting help before problems escalate. Ultimately, machine learning aspires to become a supportive tool, empowering professionals to intervene sooner and improve patient outcomes.

2. LITERATURE REVIEW

2.1 Chen et al. (2023) published "Machine Learning Approaches for Identifying Suicide Risk in Clinical Settings": This study examines research on identifying suicidal individuals using machine learning. The researchers discovered that using clinical data from electronic health records and other sources, machine learning algorithms can reliably forecast the probability of suicide.

2.2 Tao et al. (2023), "Machine Learning Approaches for Early Detection of Schizophrenia in Adolescents": This study predicted the onset of juvenile schizophrenia using machine learning. Based on clinical and demographic data, the scientists discovered that machine learning algorithms may reliably predict the beginning of schizophrenia up to two years in advance.

2.3 "A Machine Learning Approach to Identify Depression from Twitter Data" by Sharma et al. (2022): This study used machine learning to analyze tweets from individuals with depression and healthy controls. The authors found that machine learning algorithms can accurately identify depression based on linguistic features in tweets.

2.4 "Using Machine Learning to Predict Treatment Response in Depression" by Zeng et al. (2022): This study used machine learning to predict treatment response in patients with depression. The authors found that machine learning algorithms can predict treatment response with high accuracy, which could help clinicians tailor treatment plans to individual patients.

2.5 According to Shafiee et al. (2022), "Automated Detection of Cognitive Impairment in Older Adults with Depression using Machine Learning": In this work, cognitive impairment in older persons with depression was identified using machine learning. The authors discovered that using memory, attention, and processing speed tests, machine learning algorithms can reliably detect cognitive impairment.

2.6 "Machine Learning Approaches for Prediction of Treatment Response in Bipolar Disorder" written by Kim et al. (2022): In order to predict the therapy response in bipolar illness patients, this study employed machine learning. Based on clinical and demographic data, the authors discovered that machine-learning algorithms can predict therapy response with high accuracy.

3. DATASET DESCRIPTION

The dataset namely "mental-health.csv", obtained from Kaggle is typical in data analysis and machine learning. Pre-processing will be performed like missing values, duplicate values, outlier handling etc. The dataset can be download from **www.kaggle.com/mental_helath.csv.**

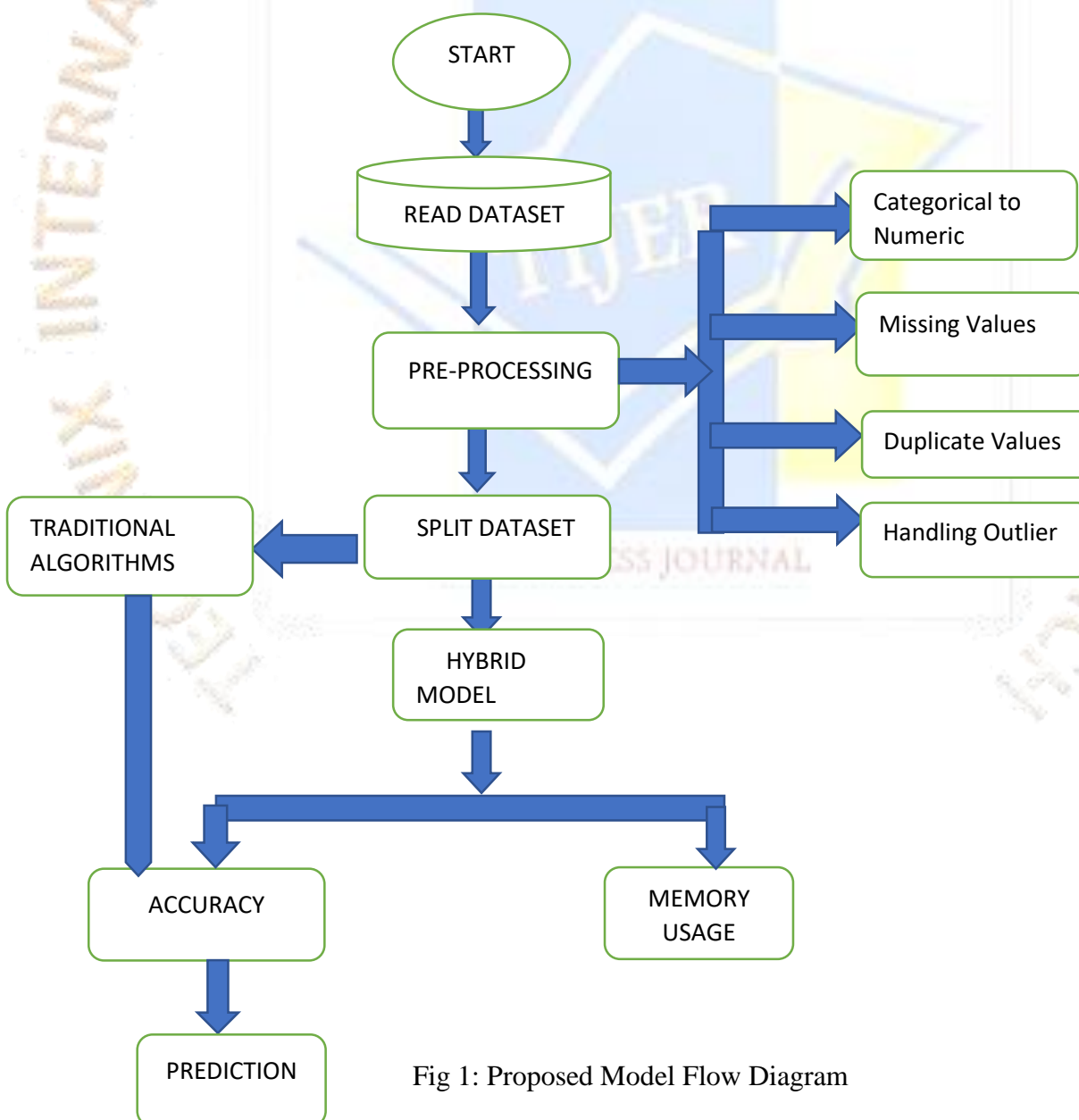## 4. PROPOSED WORK FLOW DESCRIPTION

Fig 1: Proposed Model Flow Diagram

5.   RESULT DISCUSSION

Dataset "mental-heath-in-tech-2014.csv" used that has downloaded from www.kaggle.com/datasets.Dataset have patient's record i.e.1259 and have 16 columns. First load the dataset and check patients records and features using shape command as shown in figure 2 .Also checked missing values in above-mentioned dataset. Missing record has been found as shown in figure 3.

```
[4]   # chack the shape of dataset
      data.shape

      (1259, 26)

[5]   # check null value in the dataset
      data.isnull().values.any()

      True
```

Fig 2: Records and features of Patient dataset and Missing Values

```
RangeIndex: 1259 entries, 0 to 1258
Data columns (total 26 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   Timestamp                  1259 non-null   object
 1   Age                        1259 non-null   int64
 2   Gender                     1259 non-null   object
 3   Country                    1259 non-null   object
 4   state                      744 non-null    object
 5   self_employed              1241 non-null   object
 6   family_history             1259 non-null   object
 7   work_interfere             995 non-null    object
 8   no_employees               1259 non-null   object
 9   remote_work                1259 non-null   object
 10  tech_company               1259 non-null   object
 11  benefits                   1259 non-null   object
 12  care_options               1259 non-null   object
 13  wellness_program           1259 non-null   object
 14  seek_help                  1259 non-null   object
 15  anonymity                  1259 non-null   object
 16  leave                      1259 non-null   object
 17  mental_health_consequence  1259 non-null   object
 18  phys_health_consequence    1259 non-null   object
 19  coworkers                  1259 non-null   object
 20  supervisor                 1259 non-null   object
 21  mental_health_interview    1259 non-null   object
 22  phys_health_interview      1259 non-null   object
 23  mental_vs_physical         1259 non-null   object
 24  obs_consequence            1259 non-null   object
 25  treatment                  1259 non-null   object
dtypes: int64(1), object(25)
memory usage: 255.9+ KB
```

Fig 3: Features "State",Self_employed","work_interfere" found missing values

Missing values has found and filled by using mean method. Outliers has been found and handled by using capping technique. Duplicates values has removed and except age ,all features have "object" datatype. By using label encoding, features have converted to numeric. After pre-processing, new benchmark, dataset has been prepared for further used. Data Analysis has performed by considering "Age" and   Distribution of Patients Mental illness and Normal Patients as shown in figure 4.
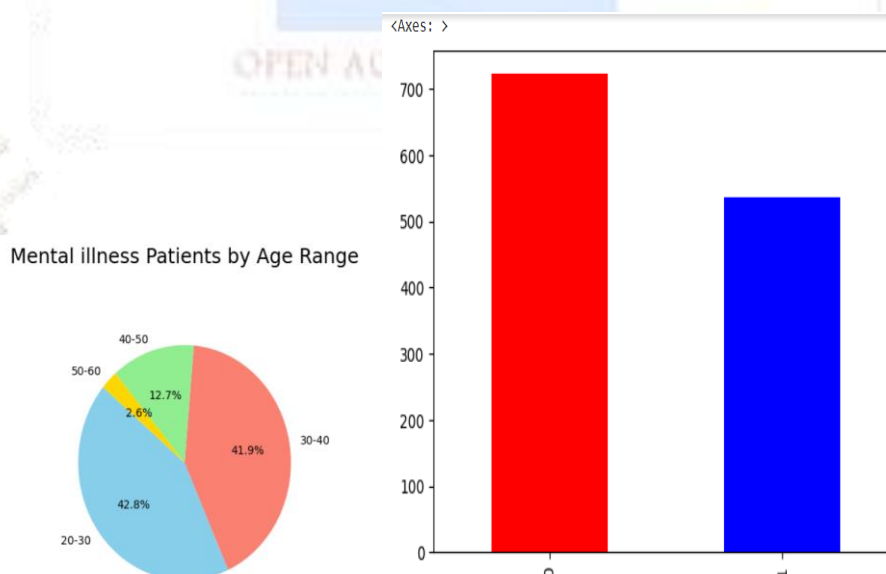

Fig 4: Data Analysis age wise found having mental illness disorder(value shown in %) and Distribution of Patients Mental illness and Normal Patients.

After data analysis, feature selection has performed by using cross validation technique. Cross validation score calculated as shown in figure 5.
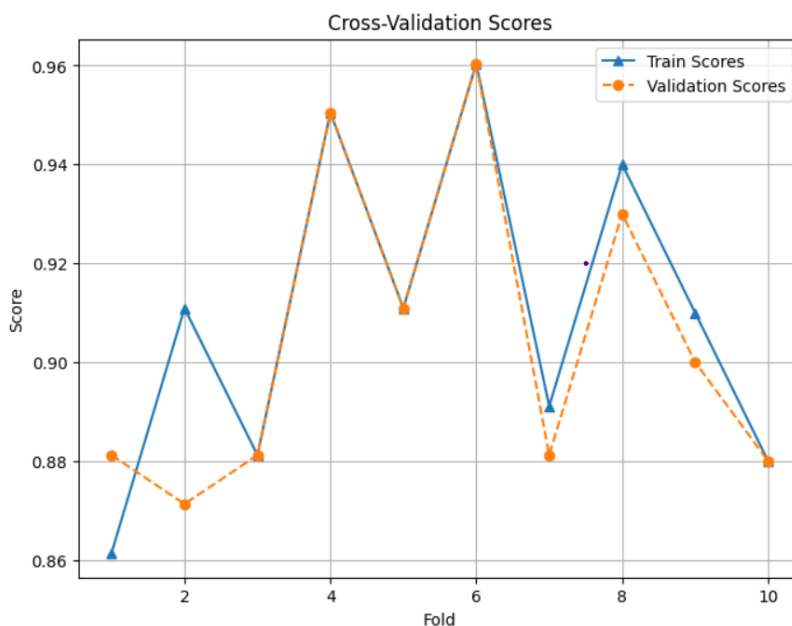

Fig 5: Feature extraction Cross Validation Score

Dataset has divided into two parts, 80% for training and 20% for testing. By using hybrid approach, obtained best accuracy more than 93%, which is better than previous work done by authors as shown in figure 7.
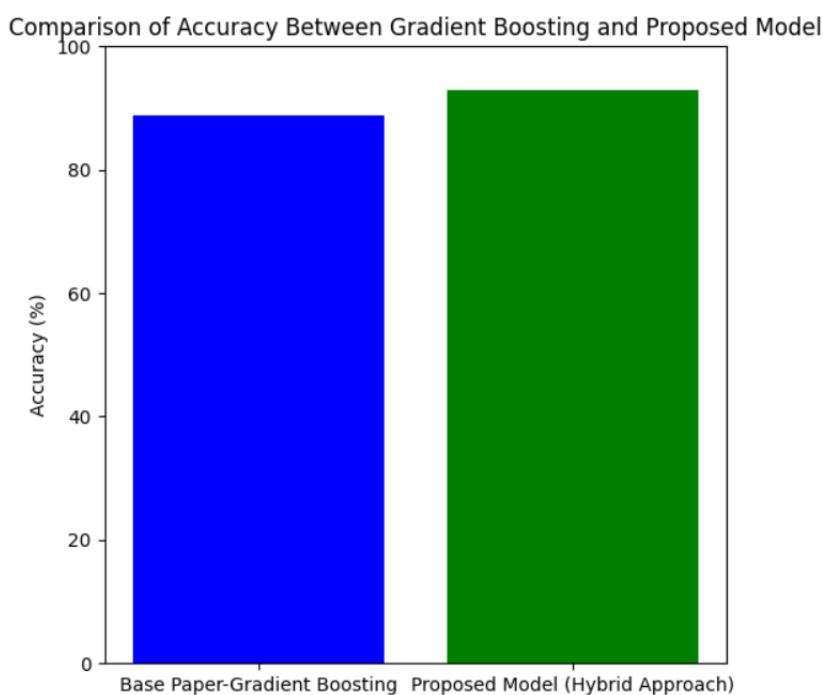

Fig 6: Comparison of Accuracy with Existing Result

6. CONCLUSION AND FUTURE WORK

In order to categorise the dataset on various mental health issues, we have examined hybrid approach of machine learning in this proposed work. The results make it abundantly evident that using a hybrid approach to machine learning techniques yields outcomes that are more accurate. Classifier has an accuracy of greater than 93%. The research employed a very small data set; however, in the future, a larger data collection may be used, and the research may be conducted using it for greater accuracy.

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