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Application of Artificial Intelligence in Psychological Evaluation of a Person using a Virtual Assistant

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Abstract: ***This paper is based on a project to develop the skills for a system to diagnose the psychological health of a person based on the inputs from a mobile keyboard or a regular keyboard. These inputs are further processed by the system and diagnosis is done accordingly. The problem we have is to convert a virtual agent i.e. a chat bot into an emotional conversational agent capable of generating a believable and dynamic dialogue in natural language. For this to happen, the dialogues convey traits of personality, emotions and its intensity. The paper proposes to make a system with whose extension the system can predict the current emotional, psychological state of an individual and respond according to the predicted result. This will create a more realistic scenario for the agent to diagnose the condition simulated by the conversational agent.***
Keywords: Conversational Agent, Virtual Assistant, Natural Language Processing (NLP), Psychology

I. INTRODUCTION

With the advancement in the information age that we have now it has become easy to store and process large amounts of data, including both structured data (Which is organized and iterative) and unstructured data (Which is raw data which could be text, prose or words). Structured data is defined as an organized database where specific information is stored based on a methodology of columns and rows while the unstructured data has no structure nor has any predefined data model or fits well into relational patterns. Furthermore, the structured information has been increasingly used as a medium by which cognitive, personality, clinical, and social psychologists attempt to understand human beings. With this our objective is to understand this unstructured data which is provided by the user and using this data provide the user with a psychological evaluation and solution to his/her current state of mind with the help of a virtual assistant viz. a chat bot or an intelligent agent.

A. Psychological Assessment

A psychiatric or psychological assessment is a process of gathering information about a person within a psychological service with the purpose of establishing a clinic diagnosis or making a cognitive evaluation. The assessment can be supplemented using ample data, including records from direct observations, responses from specific psychological tests, narratives, demographic information and so forth.

In clinical settings, psychiatric assessment is typically a multidisciplinary process involving psychologists, occupational therapists, social workers, nurses and psychometricians.

The initiative of the current research project originates from the construction of a screening system for distress among people by using the lexical features in patients' self-narratives.

These self-narratives could be text entered in various mobile applications or web browsers. The object here being to predict the current state of the person dynamically over time.

The evaluation would be administered by obtaining the logs from the user's system through their discretion. Compared to itemized questionnaires, self-narratives provide people with opportunities to express themselves freely, and they are easier to be interpreted by the specialists. In our case the role of clinicians would be done using an intelligent virtual agent. Patients may describe the traumatic events and symptoms in their own styles without limitations set by anyone. From texts, our system may understand the contents straightforwardly without having to consult a psychometrician for interpretation of the scale parameters.

The context of the present study is related to the use of language in psychological assessment. Language is the most common and the most reliable way for people to translate their internal thoughts and emotions into a form one can express and understand. With the increasing application of text-based measures, the automated identification of patients based on their self-narratives is therefore expected as a promising step toward an effective screening and diagnosis process.

B. *Research Question*

Current trends in the domain of Artificial Intelligence and business software demonstrated a few important breakthroughs in handling unstructured textual data during the past decades. A relatively promising technique for handling such unstructured data is text mining. This method exploits the information retrieval, information extraction and is a corpus-based computational linguistics based on natural language processing (NLP). The application of NLP is relatively new in psychological evaluation.
The following key challenges need to be further addressed as well as the system develops

These challenges lead to the following two main research questions:

1) How can we apply text mining to narratives collected in the framework of psychological assessment to make classification decisions?
2) How can we simultaneously model the outcome of text mining to validate the text mining procedure and enhance the quality of the measurement and classification procedure.

II. METHOD

The following concepts are the core of the evaluation system:

1) Supervised Text Classification:
a) Decision Trees
b) Naïve Bayes
c) Product Score Model
2) Chi-Square Feature Selection Algorithm
3) Sequence Model
4) LSTM

A classification framework is thus constructed. For training of the evaluation model, the model was trained over an existing dataset of responses and diagnosis done by the specialists. The dataset was randomly split into a training set and a testing set in the ratio of 70-30. For pre-processing the data and to deduct the non-informative words and normalize the words into their common lexical forms the stop word list and the Porter algorithm were used. From the training phase all the robust classifiers were extracted by using the chi-square selection algorithm. Six performance metrics, accuracy, sensitivity (recall), specificity, positive predictive value (precision) (PPV), negative predict value (NPV), and F1 measure, were used to evaluate the efficiency of the evaluation system. Accuracy, the main metric used in classification, is the percentage of correctly defined texts. Sensitivity and specificity measure the proportion of actual positives and actual negatives that are correctly identified, respectively. The words with negative semantics would be informative for detecting negative tendency in the life stories and vice versa. This data is provided as a reference to the evaluation system when it performs on the input based on the user henceforth.

A. *Proposed Architecture*

Details in Figure1. This architecture shows how the learning would take place and the phases in which it happens.

III. CONCLUSION

This evaluation system when integrated with various interactive capabilities which are at the user's disposal would prove to be a unique way for dealing with dynamic psychological evaluation and tending to all kinds of psychological health hazards if any.

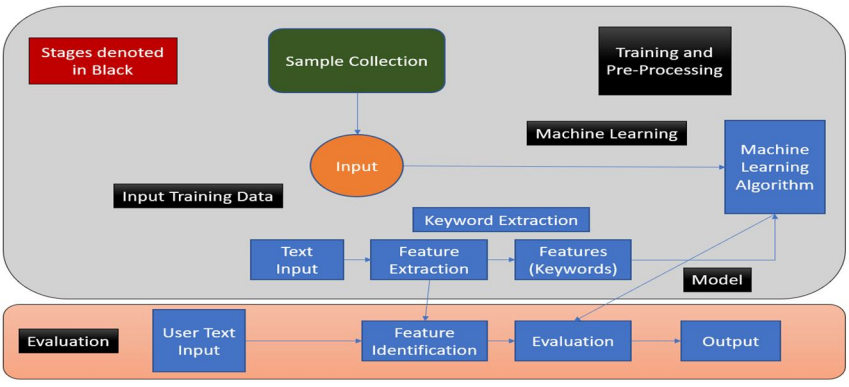

Figure 1: Proposed Architecture for the evaluation system

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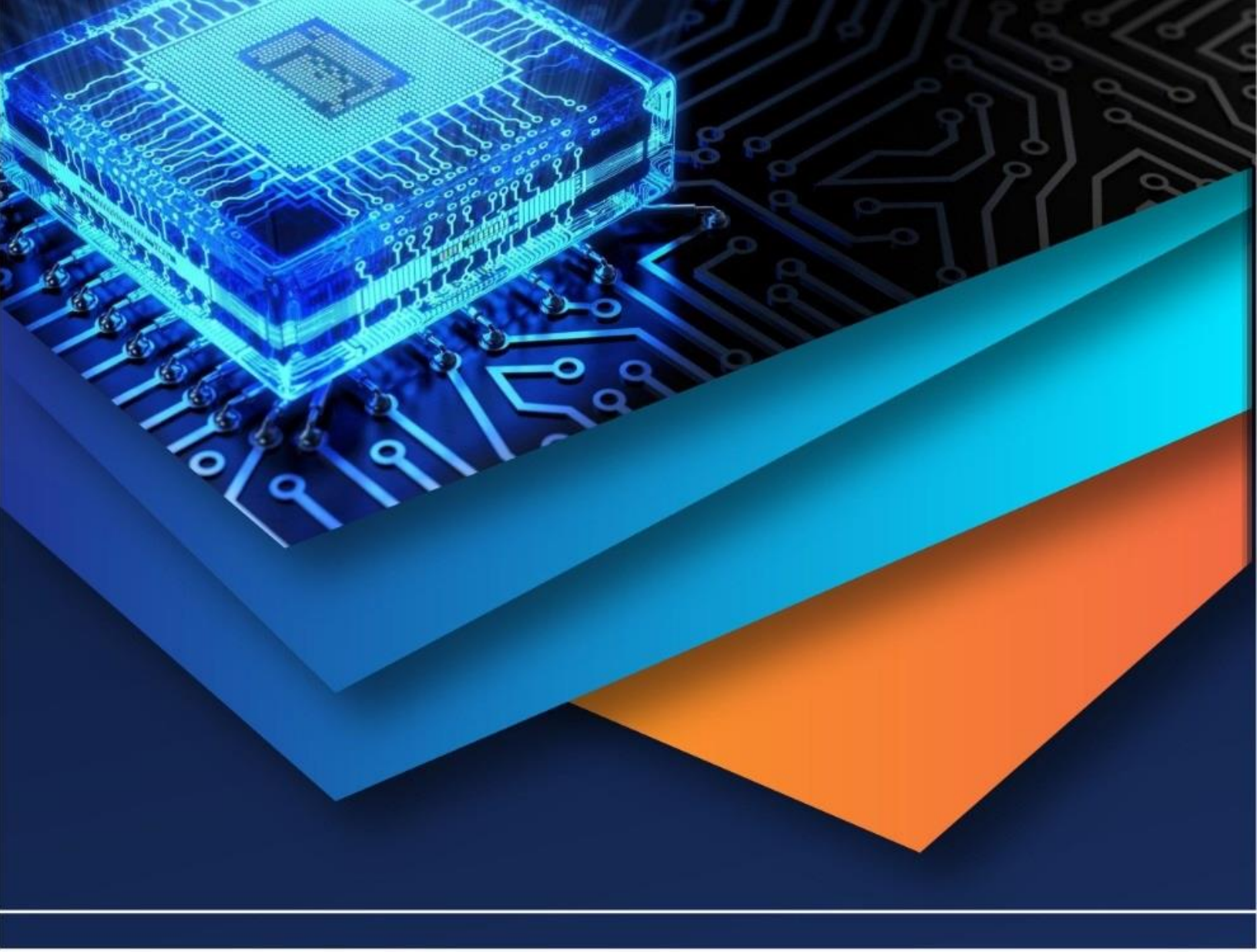

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