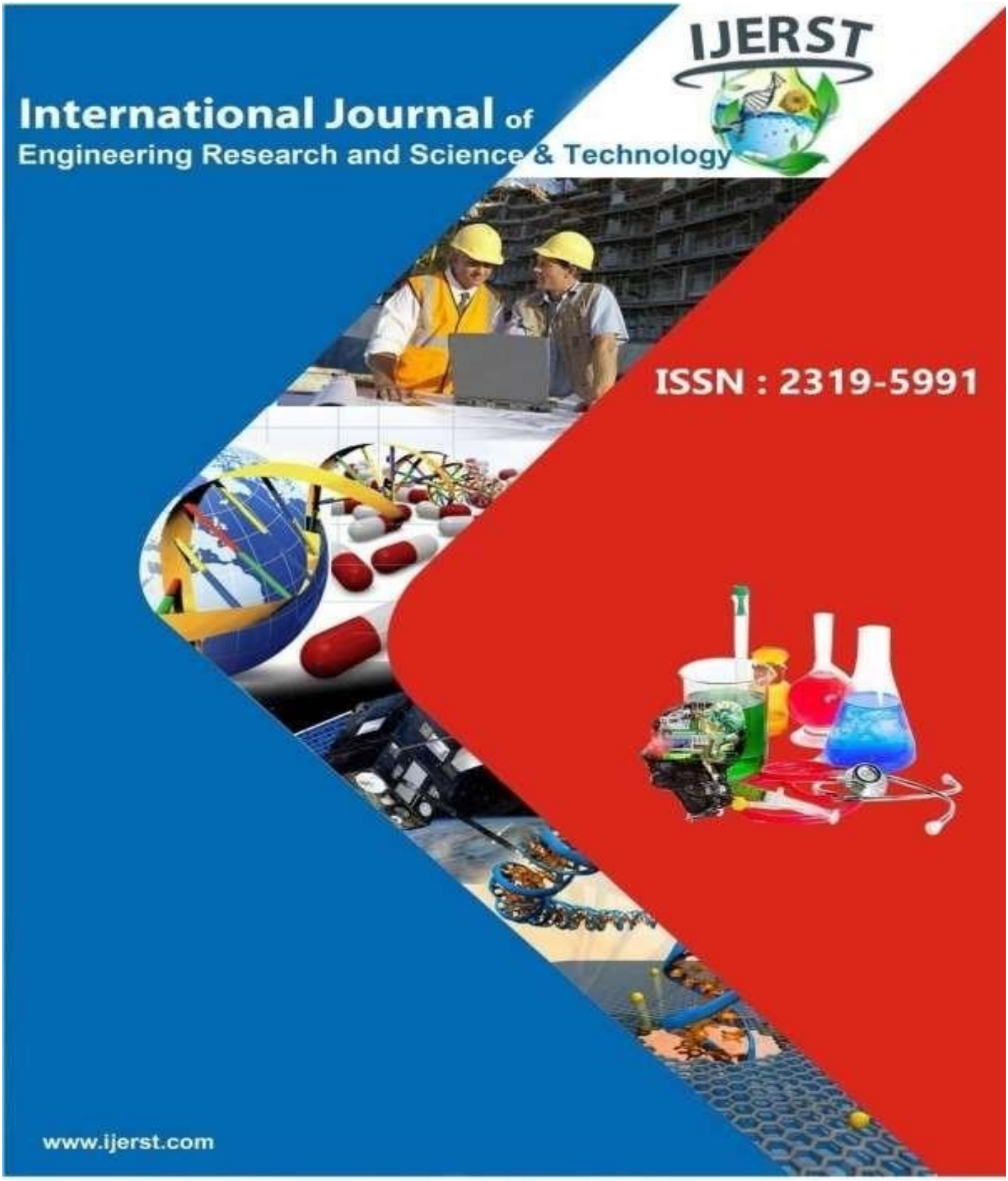

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PERSONET: AN AI-DRIVEN FRAMEWORK FOR PERSONALITY-BASED CUSTOMER SERVICE AGENT MATCHING

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ABSTRACT

Because of its many uses, personality categorisation has attracted a lot of attention in the fields of psychology, computational social science, and machine learning (ML). In order to improve customer service experiences by matching clients with appropriate support workers, this article introduces PersoNet, a novel framework designed to determine personality types using the Myers-Briggs Type Indicator (MBTI). PersoNet has an outstanding classification accuracy of over 93.98% and uses a CNN and Bidirectional Long Short-Term Memory (BiLSTM) neural network architecture. The BiLSTM + CNN design successfully captures temporal correlations and semantic complexities in textual data, which contributes to this high degree of accuracy, according to our thorough studies using the MBTI dataset. According to our experimental data, PersoNet can thus precisely choose customer care representatives that fit the personalities of its clients, resulting in a Customer Satisfaction Rate (CSR) of over 97.82%—a noteworthy increase of 20.25% in CSR. These findings position PersoNet as a state-of-the-art personality categorisation tool that significantly improves customer service quality while outperforming current techniques in terms of accuracy and computational economy.

I. INTRODUCTION

Human behaviour in many social and private contexts is governed by personality [1]. It influences a person's self-presentation [2], decision-making [3], social group selection [4], and maintenance of certain lifestyles [5]. Because of this, personality classifications are used in a variety of fields, such as predicting market demand, corporate expansion, behavior-based segmentation, forming productive teams, developing human resource management strategies, and enhancing team productivity [6]. Social interactions, IQ, actions in various contexts, and many other factors are examples of how human personality characteristics are shown [7]. And a lot of things impact it. Personality categorisation is a challenging undertaking because of the interconnectedness of these aspects while identifying the personality characteristics [8]. The creation of a revolutionary personality categorisation framework called PersoNet is examined in this research. To the best of our knowledge, it is the first time that it has been used in the proper selection of customer support agents [9]. By greatly enhancing CSR, this innovative framework shows how it has the ability to bring about a paradigm change in the Customer Service (CS) industry.

When given a user's social media postings, the PersoNet framework divides the user into one of sixteen groups based on the Myers-Briggs Type Indicator (MBTI) dataset's personality qualities [10]. Despite being created using Twitter user data, the MBTI dataset's capabilities extend beyond social media postings. This framework may be used to detect the personality in any writing that is less than 1800 characters long, including letters, autobiographical notes, and personal viewpoints. This system makes use of a well planned dataset preparation approach that is informed by mathematical analysis. Consequently, it inserts the required sequence padding values and effectively transforms any valid input into a word vector. A carefully designed and trained BiLSTM

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network, which has been optimally trained to categorise the users' personalities, is then given the word vector. The suggested PersoNet was created by mathematical analysis, in contrast to the majority of methods that randomly experiment with several Machine Learning (ML) models to see which model performs the best [11]. Learning curve analysis has even been used to optimise the dense layer's node count. Additionally, PersoNet's use in the computer science field has been investigated and examined; the results are shown in this publication.

The architecture of the suggested PersoNet for personality categorisation is amazing. In contrast to the majority of comparable studies, the network was chosen by means of a mathematical feature analysis of the dataset [12]. In this article, the BiLSTM network's characteristics have further connected with the MBTI dataset's feature analysis, which informs the network selection procedure. The BiLSTM network-based PersoNet has emerged as one of the top-performing Deep Learning (DL)-based personality classifiers because to the significant association between the dataset's characteristics and the BiLSTM network's ability to handle those features. The following is a list of PersoNet's primary innovations.

• For the first time, the CS industry is using a Deep Learning-based personality classifier architecture to increase customer satisfaction rates (CSRs).

The selection of networks that are appropriate for feature analysis with mathematical interpretation.

• The creation of a successful BiLSTM network-based framework for the efficient and precise classification of personality from relevant texts and social media postings.

With 93.98% validation accuracy, 93.83% precision, 96.2% recall, and 95.01% F1-score, an exceptional result was attained.

• Learning curve analysis is used to optimise the BiLSTM dense layer for improved performance with the best available resources.

This is how the remainder of the paper is structured: The techniques, including data collecting, data preparation, and the PersoNet design, are presented in Section II. The experimental design and outcomes are covered in Section III. Lastly, Section IV provides conclusions and suggests future paths of inquiry for this field of study.

II. LITERATURE SURVEY

Responses of the human hypothalamus-pituitary-adrenal axis to acute psychosocial stress in lab conditions,

Foley P. and Kirschbaum C.

A variety of illnesses are believed to be facilitated by cumulative acute psychosocial stress, which implies that biomarkers for the physiological response might be useful instruments for biomedical research and development. The Trier Social Stress Test (TSST), a systematic procedure for creating psychosocial stress that blends social-evaluative threat and uncontrollability, has facilitated the hunt for these biomarkers. The hypothalamus-pituitary-adrenal axis (HPAA), which is believed to be crucial in the development of stress-associated disorders, is significantly altered by this test, among other biological indicators of acute stress. The HPAA responses reveal variations across diseases and between patients and healthy persons. Furthermore, the acute stress response that the TSST triggers in an individual may also be influenced by their gender, age, personality characteristics, social context, and genetics. Longitudinal investigations are needed to characterise the roles and combinations of these elements in producing a dysregulation of the neuroendocrine responses to acute psychosocial stress.

"The cost of ethics." An economic examination of moral conduct, personality, and social norms,

Gössling, T.

The rationality of moral action and moral conviction was the main emphasis of this investigation. "Good ethics is good business" and

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"morality pays" are examples of assumptions that are not a priori correct. The institutional framework of a society and the probability that unethical activity would be accepted play a significant role in determining whether or not morality as a personal belief is also economically sensible. Therefore, political economics and the institutional framework—rules and laws—seem to be the methodical approach to morality. Nonetheless, morality is contingent upon both the official and informal frameworks of regulations and penalties. As a result, a society's culture is most strongly associated with its systematic approach to morality; societal circumstances determine how effective individual morality is. Establishing and maintaining circumstances that clearly encourage moral action is expensive for both people and society. Moral competence, education, and learning are important in this environment.

"Decision-making is only predicted by personality when information is unreliable."

G. Cowlishaw, R. Heinsohn, H. H. Marshall, and A. J. Carter

When trustworthy information about the state of affairs is available, phenotypic plasticity should be used for decision-making. However, selection should promote unresponsive behavioural phenotypes when available knowledge is incorrect, which might result in the establishment of personalities. We investigated the idea that decision-making is influenced by personality when information is faulty but not when it is trustworthy. Through repeated field tests, we quantified the behaviours of 55 wild chacma baboons (Papio ursinus) to a new meal and a moderate threat, respectively, in order to evaluate two personality traits: boldness and anxiety. We documented foraging choices in two scenarios to evaluate decision making under various information reliabilities. In order to control the dependability of the information, we observed the baboons as they foraged naturally while using trustworthy knowledge about their surroundings (>8900 judgements). We conducted an extensive in situ foraging experiment in which we gave the study troops access to experimental food patches (>10,000 choices). Crucially, the baboons received inaccurate information regarding the quality of the experimental patches as they were unable to see the food there until they closely examined them. In the presence of trustworthy signals, we observed flexible foraging choices; but, in the absence of such cues, we observed personality-dependent decisions. In particular, in the experimental setting, brave individuals were more likely to produce, whereas timid individuals were more likely to scavenge. However, under normal foraging situations, personality had no influence on foraging choices. Our findings make clear how crucial information accuracy is to the development of personality and flexibility. These results also advance our knowledge of potential future responses of individuals and groups to environmental change.

Who achieves social standing? impacts of physical appearance and personality in social groupings,

A. M. Kring, D. Keltner, O. P. John, and C. Anderson

Achieving status in the groups we belong to is one of the most significant objectives and results of social life. The degree of importance, influence, and respect that each member has in the eyes of the others determines their face-to-face status. The Big Five personality characteristics and physical beauty were linked to peer assessments of status in three studies that examined personological determinants of status in social groupings (dormitory, fraternity, and sorority). For both sexes, increased status was significantly predicted by high extraversion. Men's poorer status was predicted by high neuroticism, which is incompatible with male gender norms. Status was not predicted by any of the other Big Five characteristics. Attractiveness, which solely predicted better status in males, had no bearing on these outcomes. Despite emerging later, women's status ordering was equally as solid as men's, despite earlier assertions to the

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contrary. Personological routes to achieving status and possible mediators are the main topics of discussion.

"A tool for describing social behaviour is the riverside behavioural Q-sort,"

The Riverside Behavioural Q-sort (RBQ), developed by D. C. Funder, R. M. Furr, and C. R. Colvin, is a versatile method for compiling a broad description of how people behave in dyadic social interactions. Ratings of RBQ questions may achieve sufficient reliability to show significant correlations with a range of personality traits and to reflect the behavioural consequences of experimental interventions. Because of the RBQ's adaptability, reliability, and relative simplicity, behavioural data may be used in personality and social psychology more often.

III. SYSTEM ANALYSIS & DESIGN

EXISTING SYSTEM

In order to determine if personality-based classifications are useful in directing therapeutic therapies for adolescents with problematic sexual behaviours, Purcell et al. [16] conducted an investigation. Even though this research has been shown to be successful, no automation based on artificial intelligence (AI) is used. Based on user interactions on social media, the proposed PersoNet automatically divides personalities into sixteen groups. Quwaider et al.'s novel method [17] uses 98.6% accuracy to classify personalities into five groups based on how users behave while playing video games. Unlike social media postings, a video game-based technique does not accurately capture the emotional state. In light of this, PersonNet's application domain is broad and more useful. Greek university students' academic dishonesty varies according to their personalities, according to study by Kokkinos et al. [18]. In contrast to the suggested PersoNet, a computer-aided DL-driven automated system, this method was manual even though it may have benefited from ML models.

Pradnyana et al. [19] have investigated the customised Bidirectional Encoder Representations from the Transformers (BERT) model to categorise five personalities. This method performs much worse than the PersoNet, achieving 72% accuracy with a 71% F1-score. Furthermore, the suggested PersoNet is reliable and suitable for a worldwide audience, whereas this research is limited to Indonesian social media users. The dataset utilised in this paper's personality classification was also used by Ryan et al. [20].

They investigated the effectiveness of the extreme gradient boosting classifier, random forest, stochastic gradient descent, logistic regression, linear support vector classification, and the cat boosting classifier. They used the Synthetic Minority Oversampling Technique (SMOTE) to balance the data. Their accuracy has increased to a level of 82.82%. The suggested PersoNet outperforms this approach by a significant margin using the same dataset. Wang et al.'s Fuzzy-Logic-based method [21] models digital personality using the Mayers-Briggs Type Indicator (MBTI) dataset. In order to categorise personalities, Lin et al. [22] used the GrayWolf Optimiser (GWO) to choose features from high-dimensional psycholinguistic traits. The well-designed network topology of the suggested PersoNet, which was created after extensive mathematical study, prevented any of these methods from outperforming it.

Disadvantages

• Data complexity: In order to identify Personality Classification, the majority of machine learning models now in use need to be able to properly read vast and complicated datasets.

• Data availability: In order to provide precise predictions, the majority of machine learning models need a lot of data. The accuracy of the model may degrade if data is not accessible in large enough amounts.

• Inaccurate labelling: The accuracy of the machine learning models that are now in use depends on how well the input dataset was used for training. Inaccurate labelling of the data

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prevents the model from producing reliable predictions..

PROPOSED SYSTEM

The architecture of the suggested PersoNet for personality categorisation is amazing. In contrast to most previous studies of the suggested system, the network was chosen by means of mathematical feature analysis of the dataset. In this article, the BiLSTM and CNN networks' features have further correlated, and the network selection procedure is guided by the MBTI dataset's feature analysis. The BiLSTM and CNN network-based PersoNet has emerged as one of the top-performing Deep Learning (DL)-based personality classifiers because to the significant association between the dataset's characteristics and the network's ability to handle those features.

Advantages

• For the first time, the CS industry is using a Deep Learning-based personality classifier architecture to increase customer satisfaction rates (CSRs).

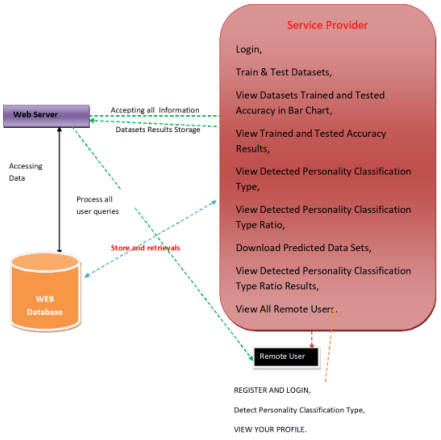
The selection of networks that are appropriate for feature analysis with mathematical interpretation.

• The creation and implementation of a successful CNN and BiLSTM network-based framework for the efficient and precise classification of personality from social media postings and associated texts.

With 93.98% validation accuracy, 93.83% precision, 96.2% recall, and 95.01% F1-score, an exceptional result was attained.

• Using learning curve analysis to optimise the CNN dense layer and BiLSTM for improved performance with the best available resources.

SYSTEM ARCHITECTURE



IV. IMPLEMENTATION

Modules

Service Provider

The Service Provider must use a working user name and password to log in to this module. Following a successful login, he may do several tasks including training and testing datasets, See the Bar Chart of Trained and Tested Accuracy Datasets. View Accuracy Tested and Trained Results, View Type of Detected Personality Classification, View Type Ratio of Detected Personality Classification, Get Predicted Data Sets here. View the results of the Detected Personality Classification Type Ratio. See Every Remote User.

View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

Remote User

A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's

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information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. Following a successful login, the user will be able to see their profile, detect their personality classification type, and register and log in.

ALGORITHMS

Logistic regression Classifiers

The relationship between a collection of independent (explanatory) factors and a categorical dependent variable is examined using logistic regression analysis. When the dependent variable simply has two values, like 0 and 1 or Yes and No, the term logistic regression is used. When the dependent variable contains three or more distinct values, such as married, single, divorced, or widowed, the technique is sometimes referred to as multinomial logistic regression. While the dependent variable's data type differs from multiple regression's, the procedure's practical application is comparable.

When it comes to categorical-response variable analysis, logistic regression and discriminant analysis are competitors. Compared to discriminant analysis, many statisticians believe that logistic regression is more flexible and appropriate for modelling the majority of scenarios. This is due to the fact that, unlike discriminant analysis, logistic regression does not presume that the independent variables are regularly distributed.

Both binary and multinomial logistic regression are calculated by this software for both category and numerical independent variables. Along with the regression equation, it provides information on likelihood, deviance, odds ratios, confidence limits, and quality of fit. It does a thorough residual analysis that includes diagnostic residual plots and reports. In order to find the optimal regression model with the fewest independent variables, it might conduct an independent variable subset selection search. It offers ROC curves and confidence intervals on expected values to assist in identifying the optimal classification cutoff point. By automatically identifying rows that are not utilised throughout the study, it enables you to confirm your findings.

Random Forest

Random forests, also known as random decision forests, are ensemble learning techniques that build a large number of decision trees during training for tasks like regression and classification. The class chosen by the majority of trees is the random forest's output for classification problems. The mean or average forecast of each individual tree is given back for regression tasks. The tendency of decision trees to overfit to their training set is compensated for by random decision forests. Although random forests are less accurate than gradient enhanced trees, they often perform better than choice trees. However, their performance may be impacted by data peculiarities.

Tin Kam Ho[1] developed the first algorithm for random decision forests in 1995 by using the random subspace technique, which in Ho's definition is a means of putting Eugene Kleinberg's "stochastic discrimination" approach to classification into practice.

Leo Breiman and Adele Cutler created an algorithm extension and filed for a trademark in 2006 for "Random Forests" (owned by Minitab, Inc. as of 2019). The extension builds a set of decision trees with controlled variance by combining Breiman's "bagging" concept with random feature selection, which was initially proposed by Ho[1] and then separately by Amit and Geman[13].

Businesses often employ random forests as "blackbox" models since they need minimal setup and provide accurate forecasts across a variety of inputs.

SVM

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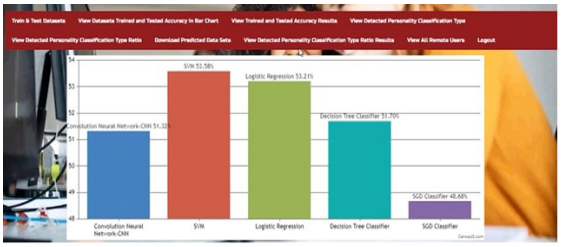
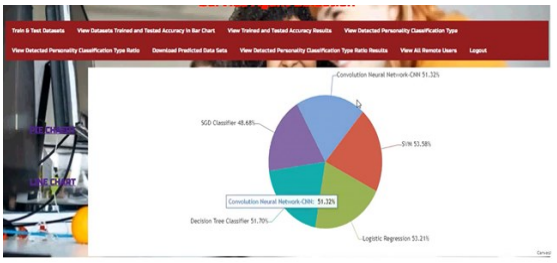
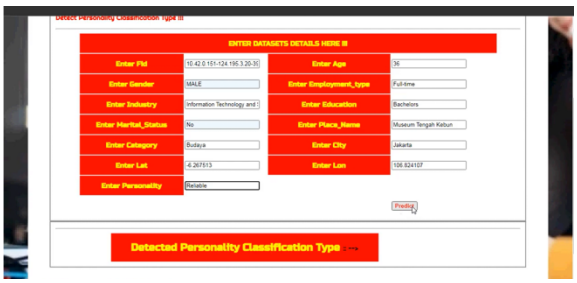
The goal of a discriminant machine learning approach in classification problems is to identify a discriminant function that can accurately predict labels for newly acquired instances based on an independent and identically distributed (iid) training dataset. A discriminant classification function takes a data point x and assigns it to one of the several classes that are part of the classification job, in contrast to generative machine learning techniques that call for calculations of conditional probability distributions. Discriminant techniques are less effective than generative approaches, which are mostly used when prediction entails the identification of outliers. However, they need less training data and processing resources, particularly when dealing with a multidimensional feature space and when just posterior probabilities are required. Finding the equation for a multidimensional surface that optimally divides the various classes in the feature space is the geometric equivalent of learning a classifier.

SVM is a discriminant approach that, unlike genetic algorithms (GAs) or perceptrons, which are both often used for classification in machine learning, always returns the same optimum hyperplane value since it solves the convex optimisation issue analytically. The initialisation and termination criteria have a significant impact on the solutions for perceptrons. While the perceptron and GA classifier models are distinct every time training is started, training yields uniquely specified SVM model parameters for a given training set for a certain kernel that converts the data from the input space to the feature space. The only goal of GAs and perceptrons is to reduce training error, which will result in several hyperplanes satisfying this criterion.

V. SCREEN SHOTS







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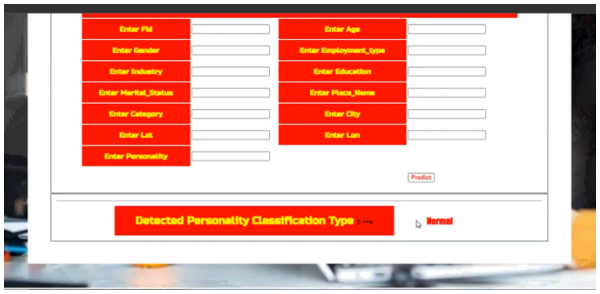

VI. CONCLUSION

In order to improve Customer Satisfaction Rate (CSR), this study presents PersoNet, a new Deep Learning (DL) framework for classifying human personalities into the 16 Myers-Briggs Personality Type (MBTI) categories. As the first to use DL in this way, PersoNet is noteworthy for its impressive 93.98% accuracy and 20.25% increase in CSR. PersoNet sets itself apart with an optimised BiLSTM network that was created using mathematical analysis and advanced data processing. Outstanding performance metrics are obtained with this method: 93.98% accuracy, 93.78% precision, 95.76% recall, and 95.43% F1-score. Consistent k-fold cross-validation findings and its advantages over comparable techniques further support its effectiveness. Although it results in a 19.49% increase in waiting time, the framework's resource optimisation is also noticeable. Despite its notable advancements, PersoNet has drawbacks, such as a limited input text length of 1800 characters and a dependence on pre-processed social media data. These issues, such as protection against adversarial machine learning attacks, will be addressed in future improvements.

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