Order N°:068

A thesis submitted to the

UNIVERSITY OF MOHAMED BOUDIAF – M'SILA

FACULTY OF MATHEMATICS AND COMPUTER SCIENCE
DEPARTMENT OF COMPUTER SCIENCE

In partial fulfillment of the requirements for the degree of

Professional Master in **Artificial Intelligence**

By

Boubaya, Samia

Chekhaba, Amina

Title of the thesis

Development of a therapeutic service Muslim: Personality Classification of Emotions Based on Text input

Under the supervision of

Amel Meliouh

Composition of the jury

Mohamed Chatra	University of M'sila	President
… … … … … … … … … …	University of M'sila	Reporter
… … … … … … … … … …	University of M'sila	Examiner

The academic year 2021/2022

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DEDICATIONS

"We are grateful to everyone who contributed to the success of writing this thesis and who guided us in our internships."

Samia Boubaya & Amina Chekhaba

"We appreciate our family members and friends who were patient with each of us and motivated us until the end."

Chekhaba Amina & Samia Boubaya

"Individually, we praise each other for our team spirit and solidarity."

Chekhaba Amina

" I would like to thank Clinical Psychologist Omar Yahya Az El-Din for guiding me in my internship at the hospital Ben Mansor."

Boubaya Samia

"I'd like to thank professor Smaili Mesouda who provided me with the resources necessary for this thesis."

Boubaya Samia

" Finally, I thank my amazing mother and my friend Wafa who have always been there for me. Their unconditional support and encouragement were of great help."

Boubaya Samia

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LIST OF ABBREVIATIONS

PTSD	Post Trauma Syndrome Disorder
IDE	Integrated Development Environment
ANNs	Artificial Neural Networks
OCD	Obsessive-Compulsive Disorder
NLP	Natural Language Processing
CON	Conscientiousness
OPN	Openness
EXT	Extraversion
AGR	Agreeableness
NEU	Neuroticism
UML	Unified Modelling Language
BI-LSTM	Bi-directional Long Short-Term Memory
NB	Naive Bayes
TF-IDF	Term Frequency Inverse Document Frequency
BoW	Bag of the Word
NLTK	Natural Language Toolkit
CRISP-DM	Cross-Industry Standard Process for Data Mining
AI	Artificial Intelligence
BERT	Bidirectional Encoder Representations from Transformers
HMA-CNN	Hazardous Materials Accident Cable News Network
BiLSTM	Bidirectional Long Short-term Memory
ANN	Artificial Neural Network
WHO	World Health Organization
SNA	social network analysis
ML	Machine Learning
DL	Deep Learning

INTRODUCTION

Healthcare is the maintenance or improvement of health via the prevention, diagnosis, treatment, amelioration, or cure of disease, illness, injury, and other physical and mental impairments in individuals[1].

We seek to build an app dedicated to psychologically type individuals using their input and emotion classification.

Our goal is to use Deep Learning for Myers-Briggs psychological character typing. Using BERT, and fast.ai for Natural Language Processing (NLP).

Personality refers to the difference in thought pattern, emotion, motivation, and behavior characteristics of individuals, which has the basic characteristics of integrity, stability, uniqueness, and sociality. [definition Personality wiki]

Personality test results are widely used in many fields such as personalized services, personalized medicine, sentiment analysis/opinion mining, and clinical psychology.

Personality theory can be divided into six schools: psychoanalysis, traits, biology, humanism, behaviorism, and cognition schools. The most commonly used personality model is the Big Five, which is the most popular in trait schools. It describes personality from five aspects: openness (OPN), conscientiousness (CON), extraversion (EXT), agreeableness (AGR), and neuroticism (NEU).

Traditional methods of personality assessment often rely on interviews or self-report scales. This method requires a significant amount of manpower and material resources, but the feedback is limited in quantity and quality.

In recent years, deep learning has made significant progress in the field of natural language processing and has become more powerful in text modeling. Moreover, with the use of large-scale training data, the recognition errors caused by deep neural networks have been significantly reduced compared to traditional empiricist approaches

The rapid development of the Internet and the popularity of social media tools, such as Facebook, microblogs, and Twitter, have made it easy for researchers to become interested in social network analysis. The development of automatic personality recognition has also been injected with great potential.

In the computer age, it is easy to obtain rich data that are generated when people use terminal devices and carry out social network activities.

Psychological research shows that there is a correlation between network data and personality characteristics [4], which reveals the user's personal information, decision-making style, and ideological tendency.

Therefore, the openness and accessibility of user text data make the corpus of personality classification tasks more abundant and provide convenience for personality modeling as well. Researchers usually collect posts from users at different stages and aggregate the scattered posts into a user personality profile for personality detection. Current research methods use a single model to encode each post independently, which ignores the dependencies between posts, and the extracted features are not comprehensive enough to fully mine the personality information in user data.

Another alternative approach is to combine scattered posts into sequences of arbitrary lengths for personality detection in a sequential or hierarchical coding manner [5,6].

However, human is a complex and variable complex, and the information contained in different text posts may contribute to different personality traits to different degrees.

Moreover, in the field of deep learning, to improve the accuracy of personality prediction, previous studies have linked the features extracted by deep neural network models with additional social network analysis (SNA) features or linguistic features. Moreover, personality detection models in existing works usually rely on increasing the depth of the network structure to extract semantic features in social texts. In this paper, we propose a hierarchical hybrid model based on a self-attention mechanism, called HMAttn-ECBiL, consisting of HMA-CNN, HA-BiLSTM, the original word embedding module, and the main contributions of this paper are as follows:

- HMA-CNN: we embed the multi-headed self-attention mechanism into the CNN architecture by dividing the text sequence into multiple regions to learn the local feature representation of each region in a cascade computation, and then gradually expand the region to model the global feature relationships hierarchically.
- HA-BiLSTM: we use the word attention mechanism to generate sentence-level feature representations. Then, we combine the scattered posts into multiple sequence fragments of the same length and use a Bi-LSTM and sentence-level attention mechanism to calculate

the temporal characteristics of the captured text sequence and the contribution of different posts to personality traits.

- HMA-CNN, HA-BiLSTM, and word embedding multiple modules perform feature fusion in a parallel manner to compensate for the limitations of features extracted by a single model, maximize the use of rich semantic information of text data, and ensure the integrity and diversity of features, thus improving the efficiency and accuracy of personality classification tasks.

The rest of this paper is organized as follows. In Section 2, we discuss related work. Then, we elaborate on the mixed model for personality classification in Section 3. In Section 4, we present the experimental process and simulation results of the comparative experiment. Finally, in Section 5, conclusions are drawn and plans for future work are proposed by summarizing the model and experimental results.

CHAPTER 1
MACHINE LEARNING, NLP, & MENTAL HEALTH DISORDERS

Introduction

In this chapter, we discuss in detail what the machine learning statistical techniques are and compare them for our objective study and learning about MBTI personality classification.

1. Mental Health History

According to a publication published in the World Psychiatry journal, mental health became its field of study in 1946 at the International Health Conference.

The World Health Organization (WHO) was created during this session. Even in the absence of psychiatric disorders, mental "well-being" is an important aspect of overall health, according to the WHO Constitution.

2. Artificial Intelligence

Artificial intelligence has become an umbrella term for applications that perform complex tasks that once required human input such as communicating with customers online or playing a game of chess. The term is often used interchangeably with its subfields, which include machine learning and deep learning.

However, there are differences. For example, machine learning focuses on creating systems that learn or improve their performance based on the data you consume. It is important to note that although all machine learning is AI, not all AI is machine learning.

To get the full value out of AI, many companies are making significant investments in data science teams. Data science, an interdisciplinary field that uses scientific and other methods to extract value from data, combines skills from fields such as statistics and computer science with scientific knowledge to analyze data collected from multiple sources.

3. Machine Learning History

The journey of AI began in the 1950s when computing power was a fraction of what it is today. AI started with the predictions made by the machine in a fashion a statistician does predictions using his calculator. Thus, the initial entire AI development was based mainly on statistical techniques.

4. Types of Machine Learning

Instead of pre-programming for machines to do, they rely on artificial norms to learn, and this is done in three different ways or strategies:

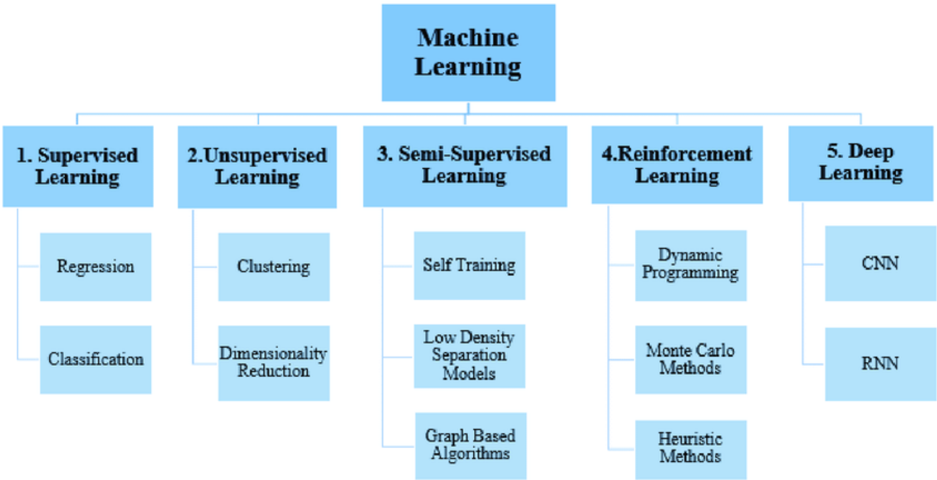

Fig. 1: Development of Machine Learning [108]

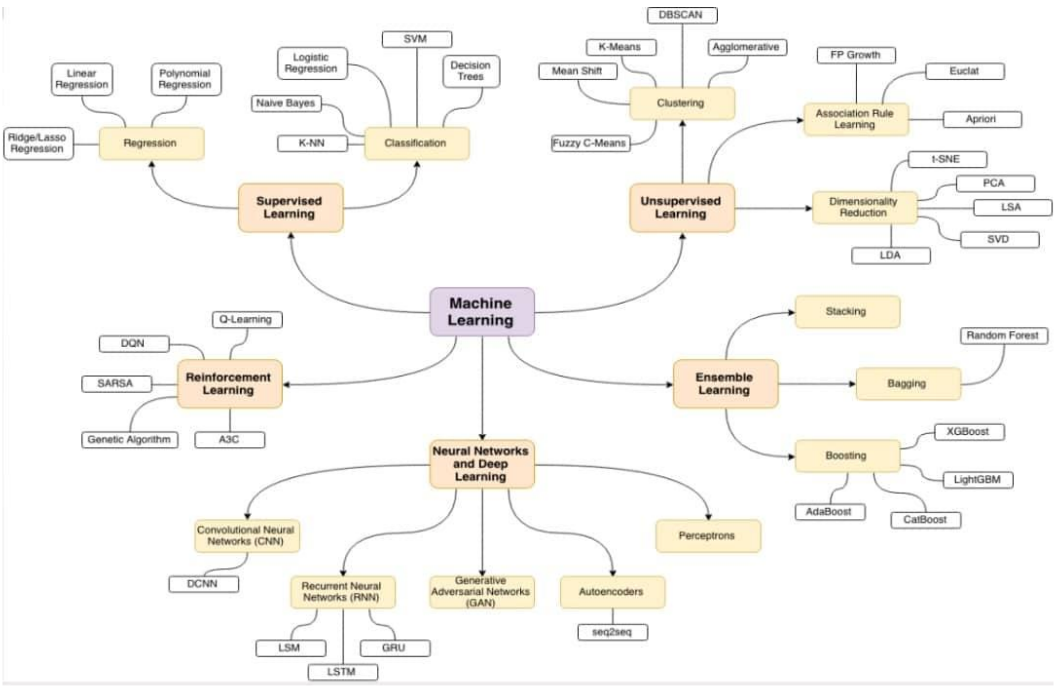

Fig. 2: Types of Machine Learning [109]

5. Basic Structure of ANNs

In English (Artificial Neural Network), it stands for ANN, and it is one of the most important inventions of the modern era. Artificial neural networks consist of a set of algorithms that simulate the advanced human brain, and manufacture electronic brains capable of learning and developing like the human brain.

What is distinguished in artificial neural networks is the presence of many layers that work on the so-called deep learning, each layer is specialized in a specific work, to explain this, let's assume that the neural network recognizes an image, a layer distinguishes brightness and a layer distinguishes shape and texture, and thus we reach the layers that deal with more accurate information Like noting a pair of eyes and ears, and finer observations of that, scientists take advantage of this learning and the machine then approximates the visual information and recognizes errors.

The idea of ANNs is based on the belief that the working of the human brain by making the right connections, can be imitated using silicon and wires as living neurons and dendrites.

The human brain is composed of 86 billion nerve cells called neurons. They are connected to other thousand cells by Axons. Dendrites accept stimuli from the external environment or inputs from sensory organs. These inputs create electric impulses, which quickly travel through the neural network. A neuron can then send the message to another neuron to handle the issue or not send it forward.

"...a computing system made up of several simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs." [109].

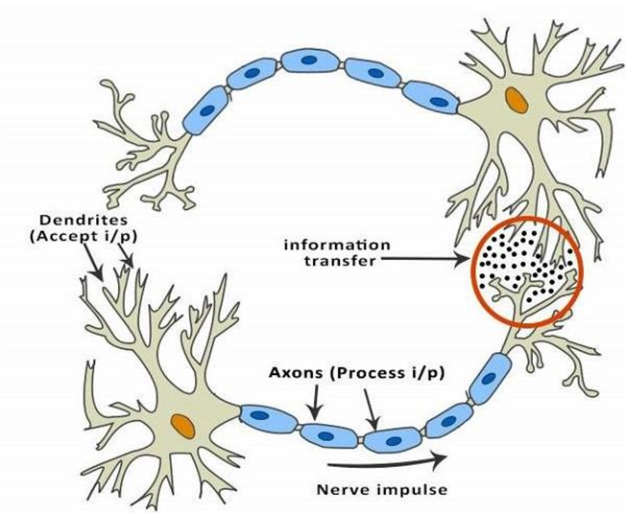

Fig. 3: Neuron [109]

ANNs are composed of multiple nodes, which imitate the biological neurons of the human brain. The neurons are connected by links and they interact with each other. The nodes can take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation or node value.

Each link is associated with weight. ANNs are capable of learning, which takes place by altering weight values. The following illustration shows a simple ANN –

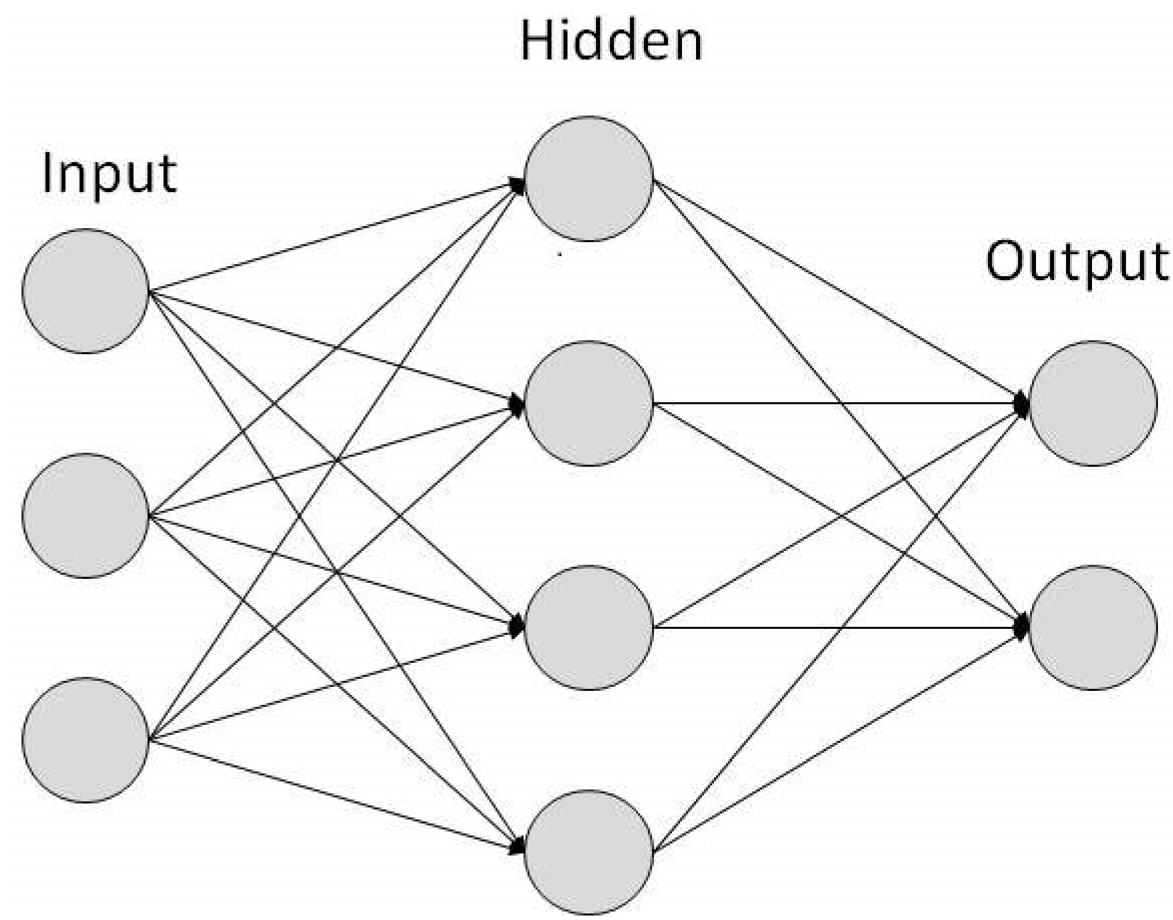

Fig. 4: Atypical ANN [109]

5.1. Components of Artificial Neural Networks

Neurons are similar in structure to the brain. It consists of nodes, similar to the nerve nodes in the human nervous system. These nodes are connected and information flows between these nodes to give this network the quality of intelligence.

The work of neurons depends on engineering sciences to carry out the functions performed by the human brain and this is different from the way the human brain works, but the result is the main feature and goal of this network which is the learning function.

Thus, the machine comes out of the constraints of dealing with a specific program to be able to receive external audio and visual signals, analyze these signals and link them to reach the realization of things and learning.

5.2. Artificial Neural Networks

The artificial ganglia are organized into parallel layers, the input, and output layers. And they are the two main layers, between the input and output layers there are many layers, each of which is specialized in a specific type of data, these layers are linked together to form a neural network.

These neurons process information and then respond. Where the information passes first in the input layer to pass on to the rest of the layers that process the information related to it, and each layer is linked to the layer that precedes it through the links of nodes to each other.

Since neural networks are similar to the human brain, this means that they are constantly changing and evolving. That is, neural networks learn and change the way they analyze data, avoiding previous mistakes.

In the topology diagrams shown, each arrow represents a connection between two neurons and indicates the pathway for the flow of information. Each connection has a weight, an integer number that controls the signal between the two neurons.

If the network generates a "good or desired" output, there is no need to adjust the weights. However, if the network generates a "poor or undesired" output or an error, then the system alters the weights to improve subsequent results.

5.3. Applications of Neural Networks

They can perform tasks that are easy for a human but difficult for a machine:

- **Anomaly Detection:** As ANNs are experts at recognizing patterns, they can also be trained to generate an output when something unusual occurs that misfits the pattern.
- **Medical:** Cancer cell analysis, fMRI, EEG, and ECG analysis, prosthetic design, transplant time optimizer.
- **Electronics:** Code sequence prediction, IC chip layout, chip failure analysis, machine vision, and voice synthesis.
- **Aerospace:** Autopilot an aircraft, aircraft fault detection.
- **Automotive:** Automobile guidance systems.

- **Military:** Weapon orientation and steering, target tracking, object discrimination, facial recognition, signal/image identification.
- **Financial:** Real estate appraisal, loan advisor, mortgage screening, corporate bond rating, portfolio trading program, corporate financial analysis, currency value prediction, document readers, and credit application evaluators.
- **Industrial:** Manufacturing process control, product design and analysis, quality inspection systems, welding quality analysis, paper quality prediction, chemical product design analysis, dynamic modeling of chemical process systems, machine maintenance analysis, project bidding, planning, and management.
- **Speech:** Speech recognition, speech classification, text-to-speech conversion.
- **Telecommunications:** Image and data compression, automated information services, real-time spoken language translation.
- **Transportation:** Truck Brake system diagnosis, vehicle scheduling, routing systems.
- **Software:** Pattern Recognition in facial recognition, optical character recognition, etc.
- **Time Series Prediction:** ANNs are used to make predictions on stocks and natural calamities.
- **Signal Processing:** Neural networks can be trained to process an audio signal and filter it appropriately in the hearing aids.
- **Control:** ANNs are often used to make steering decisions for physical vehicles**.**

6. Types of Artificial Neural Networks

There are two Artificial Neural Network topologies:

6.1. Feedforward ANN

In this ANN, the information flow is unidirectional. A unit sends information to other units from which it does not receive any information. There are no feedback loops. They are used in pattern generation/recognition/classification. They have fixed inputs and outputs.

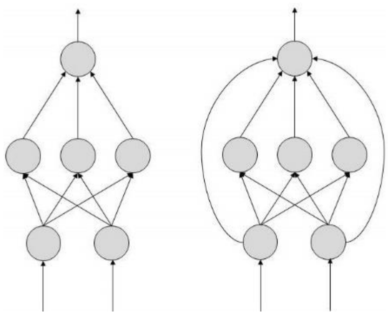

Fig. 5: FeedForward ANN [109]

6.2. Feedback ANN

Here, feedback loops are allowed. They are used in content-addressable memories.

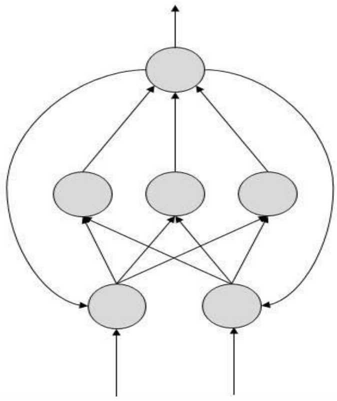

Fig. 6: Feedback ANN [109]

7. About BERT

BERT made quite some impact at the end of 2018. BERT is short for Bidirectional Encoder Representations from Transformers. You can think of it as word embeddings on steroids. Word embedding is those comparatively tiny little mappings from words to word vectors They are very powerful nonetheless. They allow you to do the math on words and texts. Finding closest words, finding opposites, and computing a numeral representation of the semantic content of a text, however, word embeddings are also quite limited in what you can do with them. BERT allows for contextual word embeddings. This means that each word is not mapped to a single vector. Rather words can be mapped to vectors that also contain knowledge about their context. You know that depending on which words are next to a single word, the meaning of that word might and usually will differ. Generally, you would use BERT in a transfer learning scenario to improve the accuracy of your Neural Network. This, of course, cuts down the required number of samples to train on in your specific use case. That is the whole deal of using pre-trained models. And it is really easy to use BERT in fastai. There is a package available called pytorch_pretrained_bert. Just a little code:

C: > Users > Firdaws > from pytorch_pretrained_bert.modeling im.py

```
from pytorch_pretrained_bert.modeling import BertForSequenceClassification
model = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=6)
```

Fig. 7: BERT Classification

8. About fast.ai.

fast.ai is on a quest to make Neural Networks uncool again. That is what the team behind it says on their homepage. One component of their crusade is fastai. No dot. Their programming library. What I liked while experimenting is the high-level building blocks approach. You just connect a couple of pieces dedicated to purposes such as data-prdata processing, evaluating, and visualization. This makes your whole programming effort quite slim.

Let us just consider the MNIST example, which I happily copy from their tutorial, because it is very speaking and very elegant. MNIST is the „Hello, world!“ of machine learning. It is about handwritten digits recognition. Here is the fastai implementation:

C: > Users > Firdaws > from pytorch_pretrained_bert.modeling im.py > ...

```
path = untar_data(URLs.MNIST_SAMPLE)
data = ImageDataBunch.from_folder(path)
learn = cnn_learner(data, models.resnet18, metrics=accuracy)
learn.fit(1)
```

Fig. 8: fast.ai. implementation

9. Machine Learning Strategies ANNs

In their quest to acquire knowledge, these systems use input from the outside world and modify information that they've already collected, or modify their internal structure. That is exactly what ANNs do. They adapt and modify their architecture to learn. [Jan 15, 2018, https://rubikscode.net › 2018/01/15 › how-artificial-neural...]

ANNs are capable of neural learning and they need to be trained. There are several learning strategies:

9.1. Supervised Learning

Supervised learning is analogous to training a child to walk. You will hold the child's hand, show him how to take his foot forward, walk yourself for a demonstration, and so o until the child learns to walk on his own.

This learning method is used when processing data for which there is no previous information about its outcome. The network analyzes the data and builds a function to determine the degree of error and reduce it as much as possible to reach the highest possible degree of accuracy.

- **Regression:**

Similarly, in the case of supervised learning, you give concrete known examples to the computer. You say that for a given feature value x1 the output is y1, for x2 it is y2, for x3 it is y3, and so on. Based on this data, you let the computer figure out an empirical relationship between x and y.

Once the machine is trained in this way with a sufficient number of data points, now you would ask the machine to predict Y for a given X. Assuming that you know the real value of Y for this given X, you will be able to deduce whether the machine's prediction is correct.

Thus, you will test whether the machine has learned by using the known test data. Once you are satisfied that the machine can do the predictions with a desired level of accuracy (say 80 to 90%) you can stop further training the machine.

Now, you can safely use the machine to do the predictions on unknown data points, or ask the machine to predict Y for a given X for which you do not know the real value of Y. This training comes under the regression that we talked about earlier.

- **Classification:**

You may also use machine learning techniques for classification problems. In classification problems, you classify objects of similar nature into a single group. For example, in a set of 100 students say, you may like to group them into three groups based on their heights - short, medium, and long. Measuring the height of each student, you will place them in a proper group.

Now, when a new student comes in, you will put him in an appropriate group by measuring his height. By following the principles in regression training, you will train the machine to classify a student based on his feature – the height. When the machine learns how the groups are formed, it will be able to classify any unknown new student correctly. Once again, you would use the test data to verify that the machine has learned your technique of classification before putting the developed model into production.

Supervised Learning is where the AI began its journey. This technique was applied successfully in several cases. You have used this model while doing the hand-written recognition on your machine. Several algorithms have been developed for supervised learning. You will learn about them in the following chapters.

9.2. Unsupervised Learning

In unsupervised learning, we do not specify a target variable to the machine, rather we ask the machine "What can you tell me about X?". More specifically, we may ask questions such as given a huge data set X, "What are the five best groups we can make out of X?" or "What features occur together most frequently in X?".

To arrive at the answers to such questions, we note that the number of data points that the machine would require to deduce a strategy that would be very large.

In the case of supervised learning, the machine can be trained with even thousands of data points. However, in the case of unsupervised learning, the number of points accepted for leading million.

These days, the data is generally abundantly available. The data ideally requires curating. However, the amount of data that is continuously flowing in a social area network, in most cases data curation is an impossible task.

This learning method is used when processing data for which there is no previous information about its outcome. The network analyzes the data and builds a function to determine the degree of error and reduce it as much as possible to reach the highest possible degree of accuracy.

The following figure shows the boundary between the yellow and red dots as determined by unsupervised machine learning. You can see clearly that the machine would be able to determine the class of each of the black dots with fairly good accuracy.

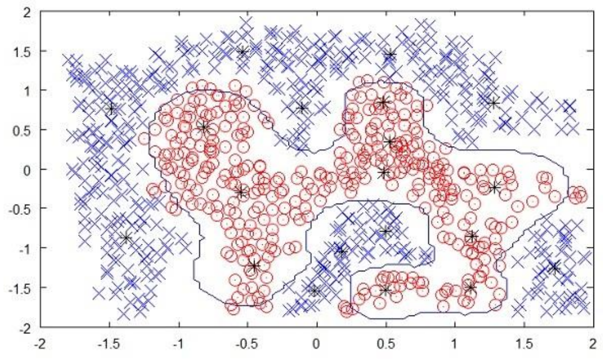

Fig. 9: Unsupervised Machine Learning [110]

Unsupervised learning has shown great success in many modern AI applications, such as face detection, object detection, and so on.

9.3. Reinforcement Learning

This learning style is based mainly on observation. Where the information is processed and the results are reached, which are estimated by the neural network.

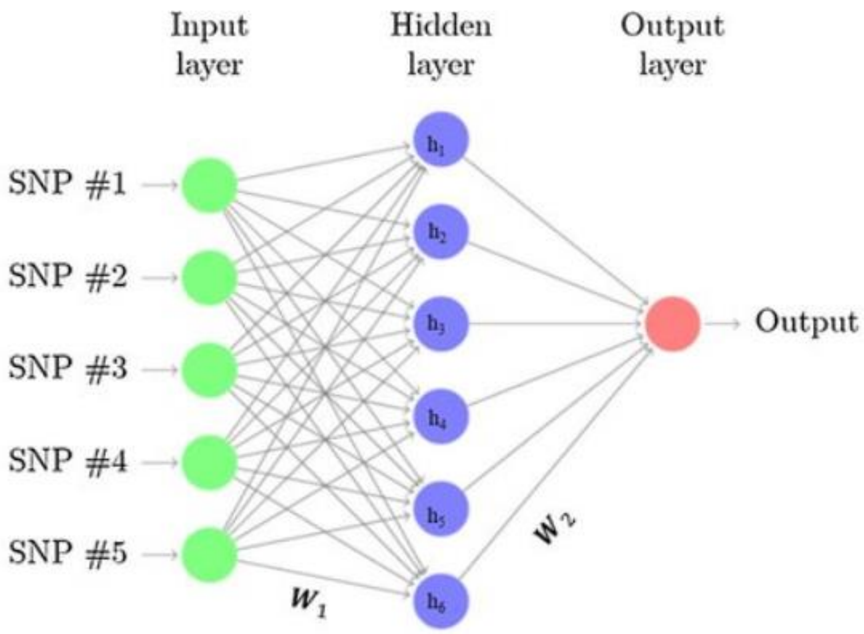

Fig. *10*: CNN [111]

9.4. Deep Learning

Deep learning is a subcategory of machine learning in which the algorithms involved are inspired by the structure and function of the brain, known as artificial neural networks.

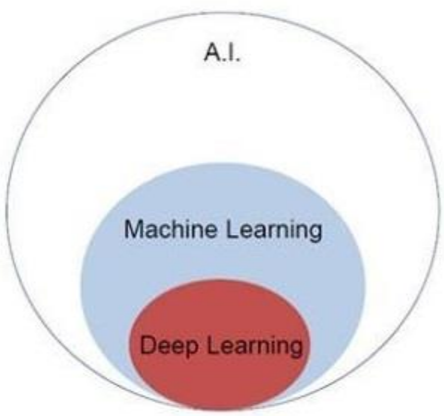

Fig. 11: Difference between Deep Learning & Machine Learning [112]

All the value of deep learning lies in the supervised learning or learning from labeled data and algorithms.

Each algorithm in deep learning goes through the same process. It includes a hierarchy of nonlinear transformation of input that can be used to generate a statistical model as output.

We consider these steps to explain the Machine Learning process:

- Identifies relevant data sets and prepares them for analysis.
- Chooses the type of algorithm to use
- Builds an analytical model based on the algorithm used.
- Trains the model on test data sets, revising it as needed.
- Runs the model to generate test scores.

Conclusion

In summary, this study was able to use applied machine learning algorithms to predict personality from social network data. Recurrent Neutral Networks' machine learning algorithms are also the best MBTI-based personality prediction model.

Companies can benefit greatly from the ability to explore candidate profiles on social networks before selecting the right employees. Restrictions The "Myers Briggs Type Indicator" in the text is only the first level for developing a personality type model. The only social network used in this project was the Personality Cafe forum. [personality café link]

Other social networks can provide useful data that can improve predictive models. When developing new software, playing sports, or building a team to fight crime, one of the most important factors to consider when joining a team is the technical position [30].

It is also necessary to consider soft skills such as thinking and personality and living environment. Future Work We plan to use Generative Pre-trained Transformer 3 (GPT-3), an autoregressive language model that uses deep learning to generate human-like text [19].

CHAPTER 2

EMOTION CLASSIFICATION & MBTI TYPING

Introduction

Today's Artificial Intelligence (AI) has surpassed the hype of blockchain and quantum computing[89]. Developers are building new Machine learning models and re-training the existing models for better results and performance. This chapter introduces machine learning and its implementation in Neuroimaging.

1. Mental health illness

The concept of mental illness is used as a synonym for mental disorder, and the American Psychiatric Association, in the latest edition of its DSM-5 Diagnostic Manual, has adopted the use of mental disorders as an approved term, which defined it As a syndrome with noticeable effects on the sufferer's awareness or ability to control his feelings or behavior, which reflects a psychological, biological, or developmental defect and mental illnesses are usually accompanied by obvious difficulties or problems in the social, functional or other important aspects, Therefore, the diagnosis of mental illness focuses on the symptoms that the patient complains of and related to his behavior and thoughts[90].

It should be noted that the expected reactions to very sad or disturbing life events are not classified as mental illnesses, for example, reactions to the death of a close person are not considered a mental illness, and it is also indicated that behaviors outside the customs of society and what people are familiar with are not psychological diseases as long as they are not accompanied by mental disorder.

2. The difference between mental health illnesses & disorders

Mental health is important throughout life, from childhood to adolescence to adulthood; It relates to a person's emotion, psyche, social life, and ability to live well. It also helps to communicate with others and make healthy life choices. It also enables dealing with stress. It is worth noting that poor mental health is often confused with mental illness, but they are two different concepts, a person may suffer from poor mental health and not be diagnosed with a mental disorder, as well as be diagnosed as injured even though he is going through periods of psychological and social well-being.

It is noteworthy that many people suffer from a poor psychological state from time to time, but it turns into mental disorders or diseases when the symptoms affect the individual’s functions and ability to exercise his activities, in addition to causing tension or repeated stress and we warn that mental illnesses are what Except for a sick condition that one should not be ashamed of; It is like any disease, such as heart disease and diabetes, and the good thing is that it is treatable where symptoms can be controlled with medications in addition to psychiatry Scientists are making efforts to expand their understanding of how the human mind works, to help patients overcome successful treatment.

3. Mental Health Disorders’ Manifestations

Most cases of mental disorders affect individuals 24 years of age and over, although they may occur in all age groups, and, can affect any individuals without distinction, regardless of age, gender, race, identity or social and religious status, and the severity of these disorders varies. Disorders, from mild that do not affect much in daily life, as in some types of phobias or phobias, to severe that may require hospitalization for treatment also, some cases may occur occasionally and intermittently and some others may be chronic.

4. Types of Mental Health Disorders

There are many types of mental illnesses that individuals may suffer from, and some of them can be stated as follows:

4.1. Psychotic Disorders

Most notably schizophrenia, in addition to many other disorders, share symptoms of detachment from reality, such as hallucinations, delusions, and loss of the ability to speak and think. In an organized manner, it is worth knowing that symptoms of separation from reality may be observed in some other psychological disorders at times.[91]

4.2. Bipolar Disorder

The sufferer goes through alternating periods of mania, hyperactivity, excessive feelings, and depression.[92]

4.3. Depressive Disorders

It affects the individual's feelings, sadness, and happiness, and may affect the ability to work.[93]

4.4. Anxiety Disorders

Generalized anxiety disorder, panic disorder, phobia, and Obsessive-compulsive.

Obsessive-compulsive disorder is defined by obsessions, thoughts, and behaviors that cause an individual to perform certain repetitive activities compulsively.[94]

4.5. Trauma and Stress Disorders

They appear when a person has to cope with certain distressing events, including post-traumatic stress disorder (PTSD) and acute stress disorder)[95].

4.6. Dissociative Disorders

Also known as dissociative disorders, here the sufferer has difficulty in sensing himself and his identity, as in dissociative identity disorder and dissociative amnesia[96].

4.7. Psychosomatic Disorders

The patient may be affected emotionally or functionally by one of the physical symptoms in his body, and these symptoms may be related to a specific disease or not related to any disease, but the patient’s reaction to the symptoms is abnormal Examples include somatic symptom disorder, illness anxiety disorder, and factitious-disorder[97].

4.8. Feeding and Eating Disorders

Affect a person's nutrition and consequently his health, such as anorexia nervosa and binge-eating disorder, also known as a binge-eating disorder[98].

4.9. Behavioral Disorders

These are difficulties in controlling one's feelings and behaviors, such as kleptomania and intermittent explosive disorder[99].

4.10. Substance-related and Addictive Disorders

They appear especially with excessive consumption of alcohol, smoke, caffeine, and illegal substances.[100]

4.11. Personality Disorders

They cause problems in an individual's life and personal relationships when a person has a persistent pattern characterized by emotional instability and unhealthy behaviors, such as narcissistic personality, antisocial personality, and severe personality disorder.[101]

5. Symptoms of one or multiple mental health illnesses

- **Depressed mood:**

Illnesses of sadness, despair, guilt and other signs of depression indicate mental illness.

- **Lack of Motivation:**

Another sign of mental illness is a lack of passion, so the motivation remains latent, and you don't receive your work, school, or even your hobbies with the same energy that you used to.

- **Mood swings:**

Mood swings between calm and angry, between complete surrender and incomprehensible agitation are all signs of mental illness.

- **Change of habits:**

A person with a mental illness experiences significant changes in daily patterns such as sleep, appetite, eating, or self-care.

- **Physical pain:**

A person with mental illness finds his body from time to time exposed to unjustified or understandable psychological pain and experiences various aches in separate areas of his body, the most important of which are headaches, muscle pain, neck, and back.

- **Stomach problems:**

The psychological patient suffers from a state of fluctuations in the digestive system, as the digestive channels are like a second brain and respond to the general mood, so the state of the digestive system changes, and the patient suffers from bad intestinal diseases.

- **Self-harm:**

The family of the psychiatric patient and his family suffer from his delinquency and his continuous speech or his actual suicide and threaten his life.

- **Social Withdrawal:**

The mentally ill person experiences a state of social withdrawal, loneliness, and a desire for solitude, which stems from his contentment with the crowding of his thoughts, his physical condition, and his shabby appearance, as he leaves himself without taking care of her.

- **Lack of focus and memory:**

There is a clear lack in concentrating, remembering, and thinking that a person with mental illness suffers, and this stems from the inefficiency of the brain and its short and medium-term memory that may have been affected by a disorder.

6. The different Treatments for Mental Disorders

Diagnosis is the first vital stage for treating addiction and mental disorders. Anyone who suffers from a mental health episode, and in light of the complexity of symptoms, the diagnosis may overlap for different disorders, and it is dangerous to make assumptions for diagnoses based on evaluation evidence because what happens to patients can get worse at any moment[102].

Treatment options vary for both psychological and mental disorders, and the difference between mental illness and mental illness is that the former is capable of definitive and complete treatment as long as it does not reach the stages of danger using different methods, including psychotherapy, drug therapy, and auxiliary treatments with support and care. As for treatment for mental illness, the patient needs more that reduces stimuli. The disease treats the symptom, not the disease because there are no definitive treatments for it.

In this case, pharmacological treatment with mood stabilizers and antipsychotics is key.

Conclusion

We conclude that every mental illness has common repeated emotions and we can classify it into an emotional wheel to determine someone’s mental disorder.

CHAPTER 3
CONTRIBUTION

Introduction

This chapter provides the research methodology provided with figures, tables, and screenshots for an explanation.

1. Research Methodology

Machine learning is used to train machines on effective handling of data. Sometimes it is difficult for humans to interpret a pattern or extract information from a vast amount of data. Machine learning is utilized in this case [13].

Generally, machine learning is grouped into three types. For instance, “supervised learning”, “unsupervised learning”, and “reinforcement learning” [32,33]. “Supervised learning” and “Unsupervised learning” are the most widely utilized and widely accepted methods [32].

The supervised machine learning algorithms are those that require assistance from a human. The training and testing datasets are separate, without overlap between them.

An output variable must be predicted or classified in the training dataset. It is expected that an algorithm would learn patterns from training data and then apply them to test data to predict or classify. “K-Nearest Neighbor (KNN)”, “Logistic Regression”, and “Stochastic Gradient Descent” are examples of classification algorithms.

Furthermore, unsupervised learning algorithms only extract a few features from the data. Then when unseen data is introduced, it utilizes previously learned features to predict the class of the new data. “K-Means”, “Mean Shift”, and “K models” are just a few examples [14].

Meanwhile, “reinforcement learning” is employed when the task at hand entails making a series of decisions that lead to a final reward. An artificial agent is rewarded or punished for the actions it takes during the training process. The goal of the learning process is to maximize total reward. “Q-Learning” and the “Markov Decision Process” are two examples of reinforcement learning algorithms.

“Personality Prediction System from Facebook Users” [10] “Facebook” has utilized Personality Prediction Systems for many years to predict a user’s personality based on their

“Facebook” functionalities [10,30,31]. For users’ personalities,” Facebook” utilized the “Big Five Personality Traits model” [31].

This model would be utilized to discover “Conscientiousness”, “Extraversion”, “Agreeableness”, “Openness”, and “Neuroticism” [10]. The researchers utilized two dataset collections in this study to predict the personalities of the users [30].

The first dataset is made up of data samples from the “myPersonality” project, while the second was built by hand [30].

Before proceeding to the next stage, English-language texts are adjusted in the pre-processing stage. The removal of URLs, symbols, names, and spaces, as well as the lowering of the case, stemming, and removal of stop words, are all part of the pre-processing steps. Slang and non-standard words in Bahasa Melayu data are replaced manually in a separate pre-processing phase before those the texts are translated to English.

In this study, traditional machine learning algorithms and deep learning were utilized to run a series of tests to predict candidates’ personality types for specifying job positions with maximum accuracy in the classification process. Traditional machine learning algorithms include “Support Vector Ma- chines”, “Gradient Boosting”, “Naive Bayes”, “Linear Dis-criminant Analysis (LDA)”, and “Logistic Regression” [30].

Deep learning implementations, on the other hand, typically employ four architectures: “Multi-Layer Perceptrons (MLP)”, “Long Short-Term Memory (LSTM)”, and “1-Dimensional Convolutional Neural Networks (1D CNN)” [30].

Experimental algorithms of “deep learning” indicated that the “MLP architecture” had the highest average accuracy in the “personality” dataset [10,30], while the “1D CNN+LSTM” architectures had the highest accuracy in the gathered dataset [10,30]. To summarize, “deep learning” algorithms can be utilized to improve dataset accuracy, even for low-accuracy traits.

2. Myers-Briggs Type Indicator (MBTI)

Research in the personality field has long piqued the interest of psychologists, and one such study was conducted on the “Myers–Briggs Type Indicator” by a psychiatrist named “Carl Jung”. Then, “Katharine Briggs” and “Isabel Myers Briggs” created the “Myers-Briggs Type Indicator” for testing personality in the 1920s, based on “Jung’s theory of psychological types” [5,8,30]. This model instrument has 16 personality types represented by a “personality types key” as shown in Fig. 1 [7]. In the “MBTI” system, for example, people classified as “INTPs” prefer “Introversion (I)”, “Intuition (N)”, “Thinking (T)”, and “Perception (P)” personality traits. We can classify the needs or the behaviors of individuals according to labels, and then the machine can learn the patterns.

As shown in Fig. 2, the preferences in four dimensions are indicated by combining the 16 personality types. Each dimension corresponds to two distinct personalities. The four dimensions are “Introversion (I) – Extraversion (E)”, “Intuition (N) – Sensation (S)”, “Feeling (F) – Thinking (T)”, and “Perception (P) – Judgment (J)” [8].

Text or related data can be utilized to extract a variety of personality-related features. We can determine a user’s “MBTI” type by analyzing their posts on the social platform utilizing “Term Frequency-Inverse Document Frequency (TF- IDF)” to detect and quantify a person’s most frequently utilized words.

Fig. 12: A chart with descriptions of each of the 16 Myers-Briggs personality types [24]

3. Recurrent Neural Networks

“Recurrent Neural Networks” are a subset of feed-forward neural networks that can send information along with time steps.

They are a diverse family of models that can perform nearly arbitrary computations [19,20]. It has been demonstrated that finite-sized “Recurrent Neural Networks” with sigmoidal activation functions can simulate a universal Turing machine in a well-known result [20]. In practice, the ability to model temporal dependencies makes “Recurrent Neural Networks” particularly well suited to tasks where the input and/or output consists of non-independent sequences of points [20,21].

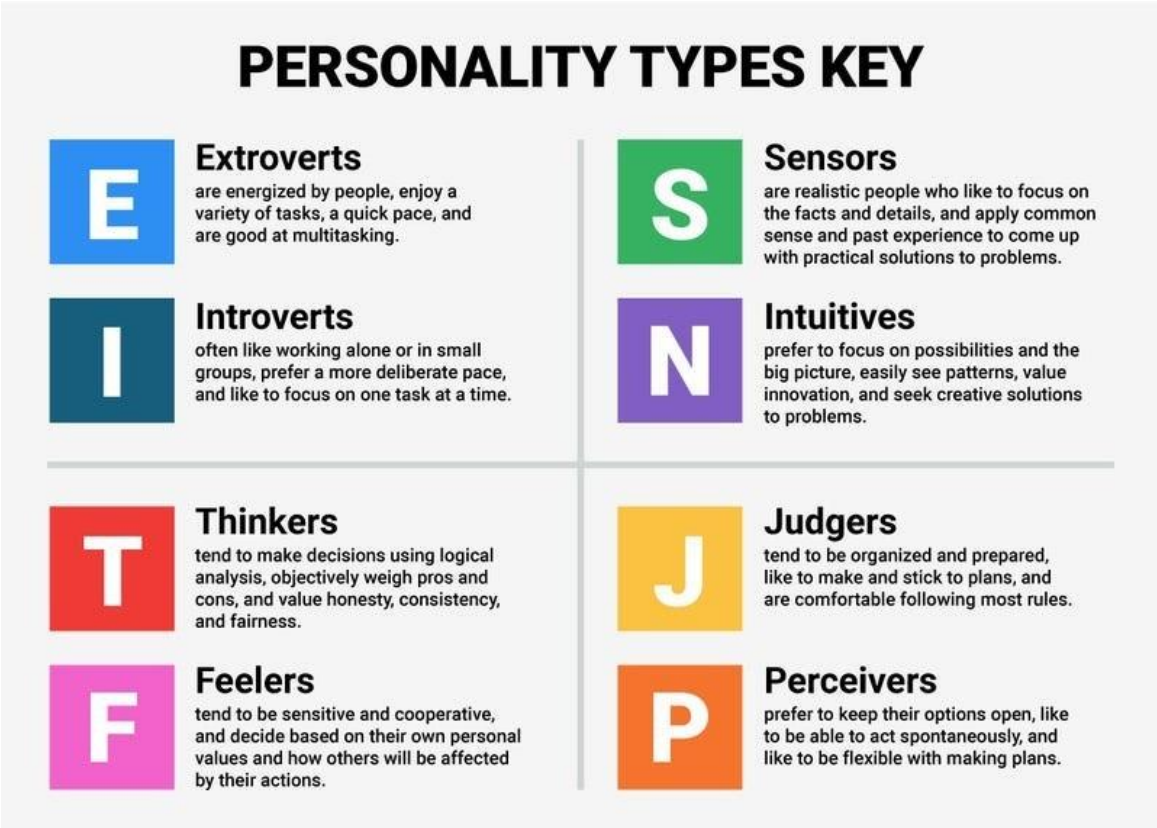

Fig. 13: Keys of Personality Types [25]

3.1. Advantages of Recurrent Neural Network

- “Recurrent Neutral Networks” can store records in such a way that each pattern is assumed to be dependent on previous ones.
- “Recurrent Neural Networks” are also utilized in combinations with convolutional layers to broaden the effective pixel neighborhood [41] [42].

3.2. Disadvantages of Recurrent Neural Network

- “Recurrent Neutral Networks” mostly have problems with exploding and vanishing gradients. It is hard to train “Recurrent Neutral Networks”.
- If tanh or ReLU is utilized as an activation function, it cannot handle very long sequences.

4. Support Vector Machine Classifiers

The “Support Vector Machines” Classifier is a supervised machine learning algorithm useful for “classification” and “regression tasks” [17,34,36].

However, it is mostly utilized in classification tasks [36]. Each data point is represented in N-dimensional space by the “Support Vector Machines” algorithm, and each feature is represented in a specific coordinate [36].

Then, it can classify the data by locating the hyperplane that best separates the two classes [18,27,34].

4.1. Advantages of Support Vector Machines

- When there is a clear margin between classes, the “Sup- port Vector Machines” perform reasonably well [35,39].
- In high-dimensional spaces, “Support Vector Machines” are more effective.
- “Support Vector Machines” are effective when the number of dimensions exceeds the number of samples [35,39].
- “Support Vector Machines” utilize a small amount of memory.

4.2. Disadvantages of Support Vector Machines

- The “Support Vector Machines” algorithm usually per- form poorly for large datasets.
- If the dataset contains noise, overlap classes, and “Sup- port Vector Machines” do not perform well [35].
- The “Support Vector Machines” may perform poorly when the number of features in each data point outstrips the sample size of the training data [35].

5. Naïve Bayes Classifiers

The Bayes theorem is the foundation of the supervised machine learning algorithm on "Naive Bayes". Each feature will contribute independently and equally to the target class or label [15,32].

Furthermore, when the likelihood of a sample belonging to a specific class is increased, then they stop interacting with one another [32]. The "Naive Bayes" classifier is easy to implement, computationally fast, and effective on large, high-dimensional datasets [16,26,32].

5.1. Advantages of Naïve Bayes

- "Naive Bayes" can be used to solve multi-class prediction problems quickly and efficiently.
- When the feature independence hypothesis is true, it can outperform other models while requiring substantially less training data.

5.2. Disadvantages of Naïve Bayes

- "Naive Bayes" presupposes that all characteristics are independent, which is seldom the case. This restricts the algorithm's usability in real-world use applications [40].
- This approach encounters the "zero-frequency problem" in which it assigns zero probability to a categorical variable whose category is in the test data set [40]. Also, it was not included in the training dataset [40].
- Because its predictions might be inaccurate in some instances, its probability outputs should not be taken too seriously.

6. Cross Industry Standard Process for Data Mining (CRISP-DM)

A schematic of "Cross Industry Standard Process for Data Mining (CRISP-DM)" is shown in Fig. 12. It is a free model that has become the industry standard in data mining methodology [38]. Because of its industry and tool independence, "CRISP-DM" can give instructions for the structured execution of any project. All scheduled tasks are often divided into six separate periods [11, 38]:

- **“Business Understanding”:** Learn the domain, clarify the goal, and plan [22].
- **“Data Understanding”:** Understand the data in all aspects [22].
- **“Data Preparation”:** Pre-processing and feature engineering [22].
- **“Modelling”:** Build the model [22].
- **“Evaluation”:** Evaluate model performance [22].
- **“Deployment”:** Deploy the model to end-users [22].

The cycle process serves as a good overall framework for an end-to-end data science product [22]. However, when tied to a product cycle, particularly in the case of a modeling product, things become more complicated; this is where agile data science can come into play [22].

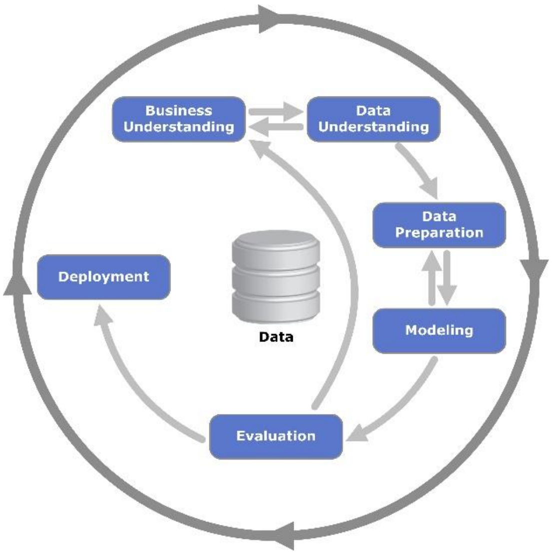

Fig. 14: “CRISP-DM” process framework diagram [23]

7. Agile Methodology” with “CRISP-DM”

The agile development process is a development cycle that has been reduced to a bare minimum [22]. The key to agile data science is, to begin with, a minimal viable model as a baseline, then refining the model through multiple iterations. We may not build the perfect model during this process, but we will deliver a model with business value. In each sprint of our project, we utilize “Agile methodology” and “CRISP-DM” as shown in Fig. 12.

8. Dataset

The "MBTI" dataset is shown in Fig. 9, which is publicly available on "Kaggle" [12] and contains 8675 rows of post data. Each row has two columns, which are the personality type based on "MBTI" and personal social networking posts from "personalitycafe.com". Users first complete a questionnaire that determines their "MBTI" type.

Then, it allows them to publicly chat or forum with other users. since each user has fifty posts available to them. There are 430,000 data points in total. The data in each row contains the following: Type (This person's 4-letter MBTI code/type). A section from each of their last 50 posts (each entry separated by " | | | " (3 pipe characters)) [12].

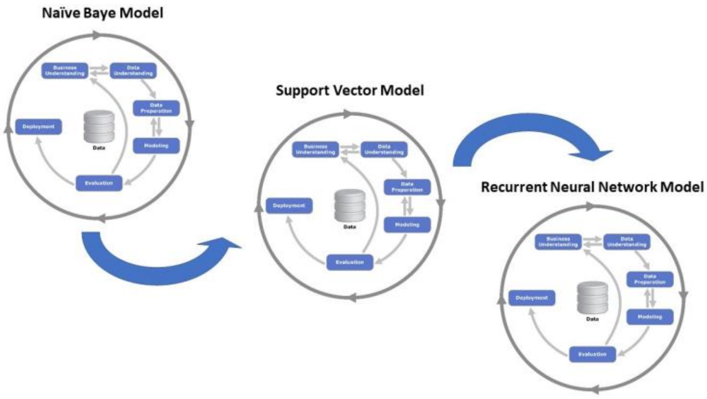

Fig. 15: "CRISP-DM" process framework with Agile Development diagram [23]

9. Exploratory Data Analysis

The objective of the exploratory data analysis was to use various tables and graphs to generate a visual representation of the data for further investigation. As shown in Fig. 5, the proportionality of the "MBTI" type is shown for the general population.

There is a significant imbalance in the "Introversion (I) Extroversion (E)" and "Intuition (N) - Sensing (S)" pairs. On the other hand, "Perception (P) - Thinking (T)" and "Judgment (J)" pairs are quite balanced. Then, we categorized the personality type keys into four dimensions as shown in Fig. 6.

In the first category of "Extroversion (E) – Introversion (I)", the distribution of "Extroversion (E)" is significantly bigger than that of "Introversion (I)". In the second category, "Sensation (S) – Intuition (N)", "Sensation (S)" has a significantly higher dispersion than "Intuition (N)". In the third category, "Thinking (T) – Feeling (F)", "Thinking (T)" has a somewhat greater distribution than "Feeling (F)". Lastly, in the fourth category, "Judgment (J) – Perception (P)", and "Judgment (J)" is more prevalent than "Perception (P)".

Then, for the concepts that were used the most frequently by specific classes of the personality dimensions, we constructed word clouds. They were created by deleting postings that had the most extreme class probability prediction. The size of each term in the word clouds is then proportional to its frequency of appearance in the top posts. We feel that these word clouds reflect some of the unique ways that different “MBTI” utilize language, as shown in Figs. 7 and 8.

10. Pre-processing

To better comprehend the datasets, we included four more columns that were categorized based on respondents’ re- responses to the four dimensions of “MBTI”: Introversion (I) - “Extraversion (E)”, “Intuition (N) - Sensation (S)”, “Feeling (F) - Thinking (T)”, and “Perception (P) - Judgment (J)”. The purpose of the procedure is to improve the accuracy of “Naïve Bayes”, “Support Vector Machines”, and “Recurrent Neutral Networks”. When we added four columns to the four dimensions of “Recurrent Neutral Networks”, we utilized those variables as one-hot encodings with “pd.get dummies()”. values.

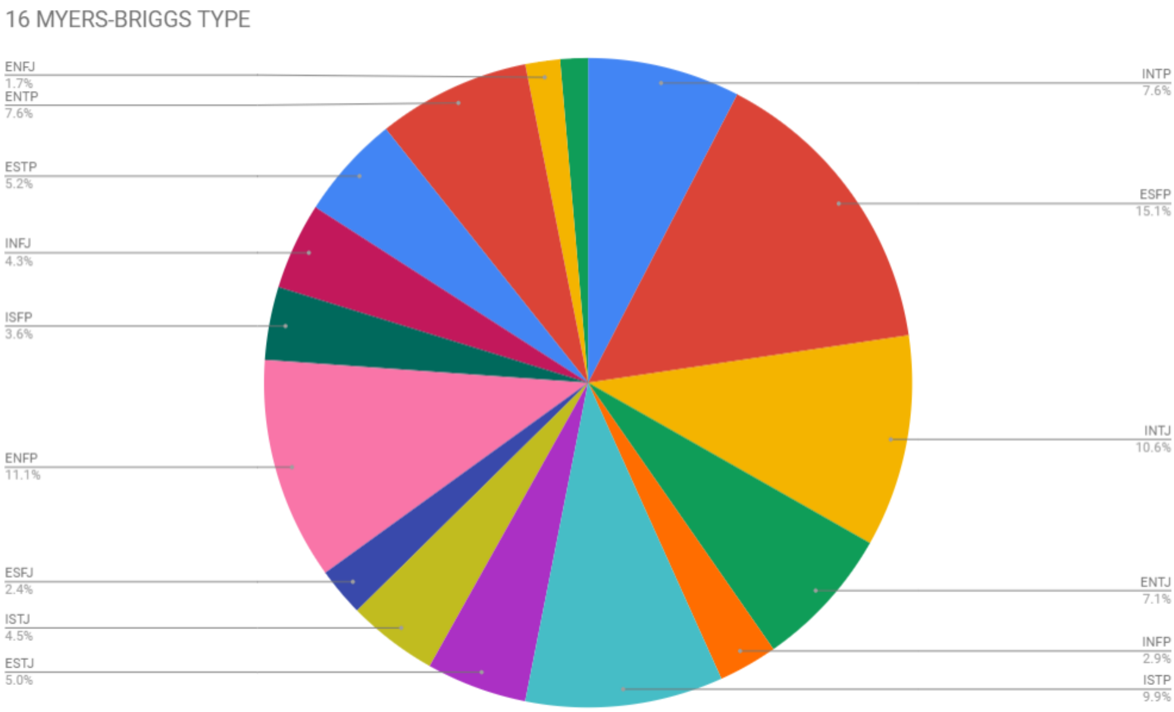

Fig. 16: Percentage of occurrence for each MBTI personality type [113]

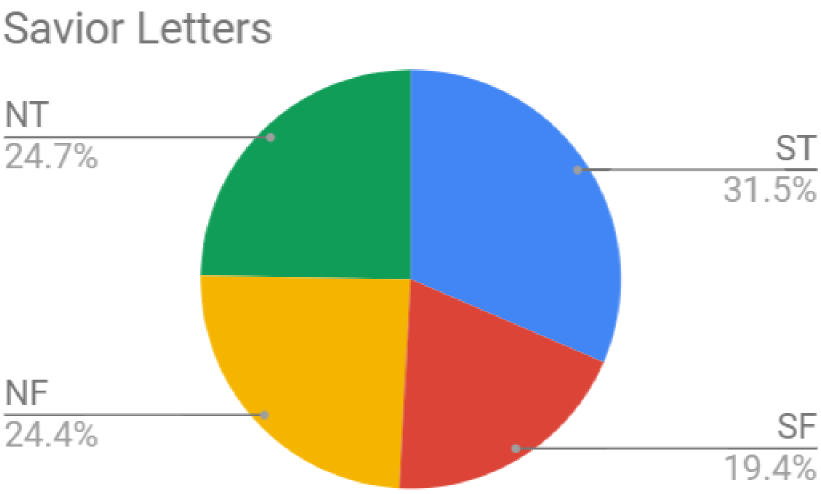

Fig. 17: Proportionality diagram of each "MBTI" type key [113]

Fig. 18: Unique word cloud for overall "MBTI" types [114]

11. Selective Word and Character Removal

Since the post data comes from a chat/forum named “per- sonalitycafe.com” where people communicate solely through written text. We removed some data points that contained links to websites because we wanted our model to be generalized in the English language.

Also, we utilized “Python’s NLTK (Natural Language Toolkit)” to remove so-called “stop words” from the text. “NLTK (Natural Language Toolkit)” is a Python package for natural language processing.

12. Lemmatization

We will look at how inflected forms of the root word are transformed into dictionary forms. To lemmatize the text, we utilized “nltk.stem.wordNetLemmatizer”.
This allows us to take advantage of the fact that inflections still have a single shared meaning.

13. Tokenization

13.1. Tokenization for “Naive Bayes” and Support Vector Machines Classifier

We tokenized the words that had been transformed in the lemmatization process by utilizing an “NLTK word tokenizer”. That is, the common word is divided into small fractions of text. Then, we change the text to frequency by a “Bag of the Word (BoW)” and “Term Frequency-Inverse Document Frequency (TF-IDF)” to examine the relevance of keywords to documents in the corpus [28,37].

13.2. Tokenization for “Recurrent Neutral Networks”

We tokenized the words that had been transformed in the lemmatization process by utilizing a “Keras word tokenizer”. That is, the common word will change to be in position 1, position 2, and so on until 74,870 in total, respectively. Any other words that have been removed will now be in the form of lists of integers with a vocabulary of 1–74,870. Then, we change texts to sequences with 72,000 number words and pad the sequence with a max length of 200.

14. Data Splitting

To assess the correctness of the "MBTI" personality model, the dataset was separated into two parts: training and testing. Utilizing the "train-test split" function in the "Scikit-learn" package, we segregated 75% of the data for training and 25% for testing. The testing dataset is a collection of previously unknown data that is solely utilized to evaluate the efficiency of a specific desired classifier.

15. Classification Tasks

We can divide the classification task from 16 classes into binary classes. Each binary class represents a unique dimension of personality as theorized by the "Myers-Briggs Type Indicator". In terms of the "Naive Bayes" and "Support Vector Machines", we imported the "Scikit-learn" library to generate those. Also, we utilized TensorFlow to create "Recurrent Neural Networks". Then, utilizing the "Scikit-learn" library's train-test split" function, the datasets were divided into "75% training" and "25% testing sets" for making a prediction, and the "Myers-Briggs Type Indicator" was trained individually. To begin with, we remove all columns that are unrelated to our features.

16. Modeling on "Naïve Bayes" and "Support Vector Machines" Classifiers

We utilized "Scikit-learn" to construct the "Naive Bayes" classifier, which is a "multinomial-NB probabilistic" learning method that is commonly utilized in "Natural Language Processing (NLP)". It computes the likelihood of each tag for a given sample and outputs the tag with the highest likelihood. Second, we utilized "Support Vector Machines" with regularization parameter with cost with 1, kernel parameter is linear with degree 3, and we also applied gamma with auto to avoid exact match as per the training data set, which tends to cause over-fitting.

17. Modeling on “Recurrent Neural Networks”

As shown in Fig. 10, we utilize the embedding word to define the indexes into dense vectors of fixed size with a total length of the vocabulary of 256. We decided to utilize “CONV1D” on “Recurrent Neural Networks” because “CONV1D” moves along a single axis.

It makes perfect sense to apply this type of convolution layer to sequential data, such as text. Then, as shown in Fig. 11, to improve the performance of the “Recurrent Neural Networks” model, we added “Bi-directional Long Short-Term Memory (BI-LSTM)” with a size of 64, allowing the “Recurrent Neural Networks” to store sequence information in both directions, backward (future to past) and forward (past to future).

18. Results and Discussion

Table I shows that the “Recurrent Neural Networks” outperform other machine learning models in terms of accuracy in all four personality types.

The accuracy of “Recurrent Neural Networks” is significantly higher than that of “Naive Bayes” and “Support Vector Machines” for all categories. On the other hand, the accuracy of “Naive Bayes” and “Support Vector Machines” for “Perception (P)” and “Judgment (J)” is significantly lower than that of the “Recurrent Neural Networks”.

As a result, the “Recurrent Neural Networks” outperform the other three machine learning models on this dataset.

	A	B
1	Type	Text input
2	INFJ	Itâ€™s okay to shut the rest of the world out. Weâ€™ll be okay. We want you to be okay too.
3	ESTP	We want you to know that youâ€™re important.
4	ISFJ	So have the door be as heavy as you want it to be. Weâ€™ll be right here, and weâ€™re prett
5	ENTJ	I have stayed out of twitter for a year and a half now because I just keep seeing rants of my fr
6	ISFP	So does anyone here have that feeling where they really wanted to get out of social media (t
7	ENTP	PS: I really wanted to delete IG too but I just left my last job and itâ€™s the only way I could c

Fig. 19: “MBTI” Personality Type Dataset [12]

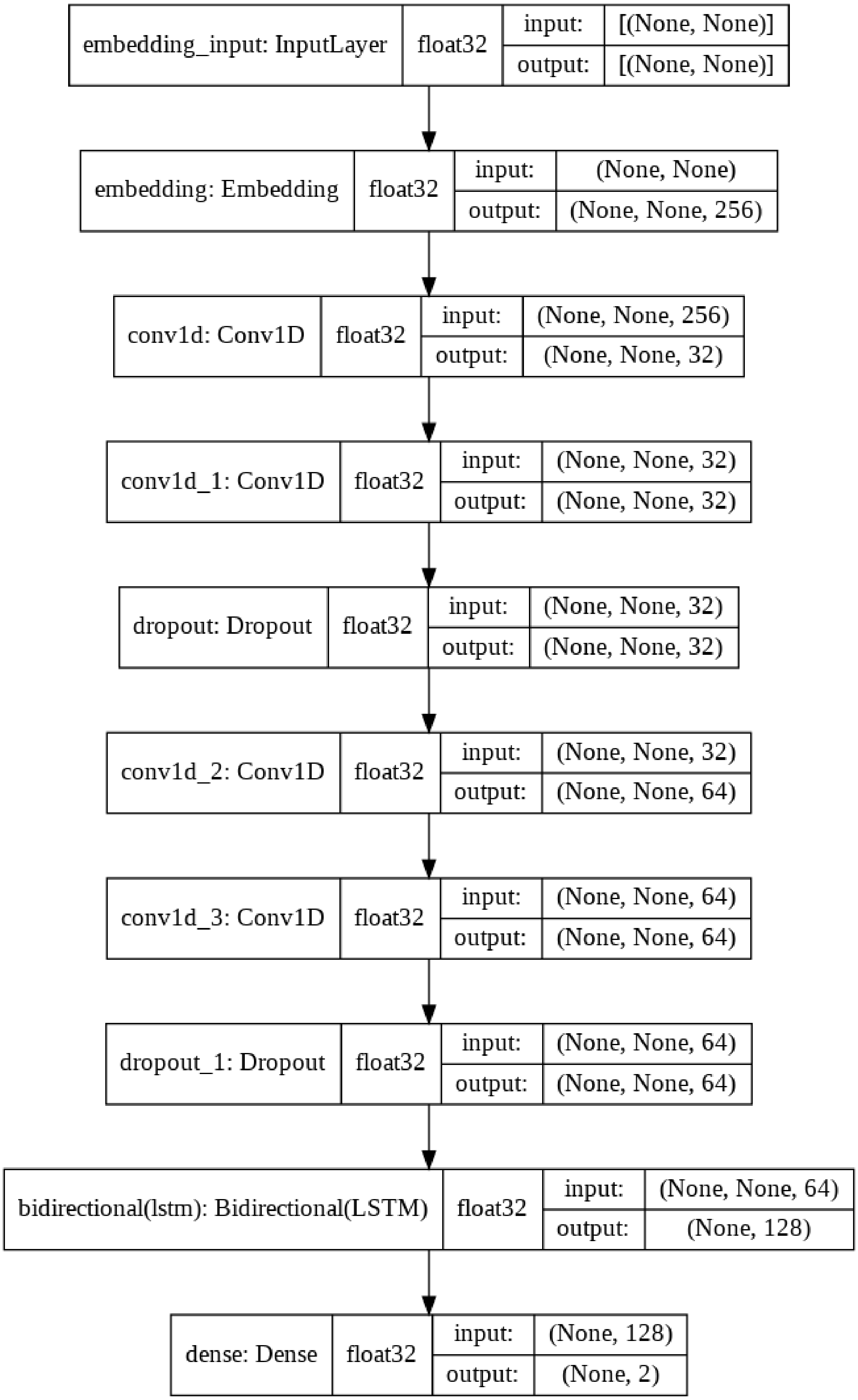

Fig. 20: Recurrent Neural Networks Architecture [107]

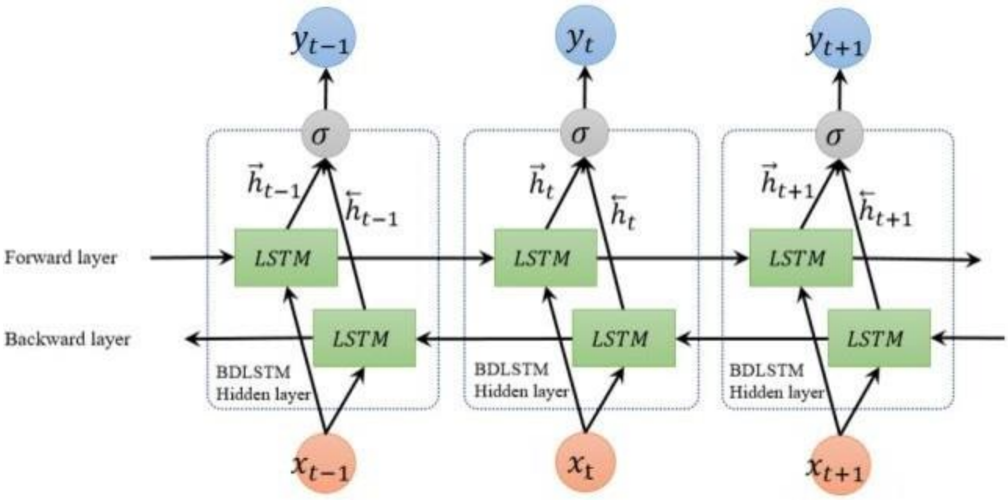

Fig. 21: Bi-directional Long Short-Term Memory (BI-LSTM) Architecture [29]

TABLE I
ACCURACY OF SUBSET "MBTI" MODEL

Model	Type			
	I/E	N/S	F/T	P/J
"Naive Bayes"	78.28%	86.95%	80.63%	74.78%
"Support Vector Machines"	82.15%	87.32%	80.49%	72.70%
"Recurrent Neural Networks"	83.59%	93.22%	80.00%	77.40%

TABLE II
OVERALL ACCURACY OF "MBTI" MODEL

Model	Overall Accuracy
"Naive Bayes"	41.03%
"Support Vector Machines"	41.97%
"Recurrent Neural Networks"	49.75%

Table 1: Accuracy of subset "MBTI" MODEL [38]

In contrast with the overall accuracy in each model shown in Table II, there appears to be a general weakness in our model's ability to classify all four "MBTI" dimensions accurately. However, the number that represents perfect classification does not indicate the efficacy of our model's predictions of overall "MBTI" types.

Since the "Recurrent Neural Networks" outperform, the confusion matrix of the "Recurrent Neural Networks" model is shown in Fig. 12. For each "MBTI" model, the results are mostly positioned as "True Positive" which means they are projected as positive and turn out to be true. which is a false positive, implying that the prediction is positive but incorrect.

Lastly, the classification report of the "Recurrent Neural Networks" is shown in Fig. 13 and Fig. 14. This shows that the F-score or F-measure, which is a weighted average score of the true positive (recall) and precision, is around 76% when calculated as the mean of all models.

P/J model		
Actual \ Predicted	J	P
J	764	79
P	411	915

N/S model		
Actual \ Predicted	N	S
N	1800	83
S	64	222

I/E model		
Actual \ Predicted	E	I
E	423	95
I	261	1390

F/T model		
Actual \ Predicted	F	T
F	774	359
T	76	960

Table 2: Confusion Matrix on each "MBTI" model with RNN[60]

I/E model				
Classes	Precision	Recall	F1-score	Support
E	0.62	0.82	0.70	518
I	0.94	0.84	0.89	1651
accuracy			0.84	2169
macro avg	0.78	0.83	0.80	2169
weighted avg	0.86	0.84	0.84	2169
F-measure: 0.7952				

F/T model				
Classes	Precision	Recall	F1-score	Support
F	0.91	0.68	0.78	1133
T	0.73	0.93	0.82	1036
accuracy			0.80	2169
macro avg	0.82	0.80	0.80	2169
weighted avg	0.82	0.80	0.80	2169
F-measure: 0.7980				

Table 3: Classification Report on each "MBTI" model with RNN (1) [57]

N/S model				
Classes	Precision	Recall	F1-score	Support
N	0.97	0.96	0.96	1883
S	0.84	0.35.	0.50	286
accuracy			0.90	2169
macro avg	0.85	0.87	0.86	2169
weighted avg	0.93	0.93	0.93	2169
F-measure: 0.7211				

P/J model				
Classes	Precision	Recall	F1-score	Support
J	0.65	0.91	0.76	843
P	0.92	0.69.	0.79	1326
accuracy			0.77	2169
macro avg	0.90	0.89	0.89	2169
weighted avg	0.82	0.77	0.78	2169
F-measure: 0.7730				

Table 4: Classification Report on each “MBTI” model with RNN (2) [57]

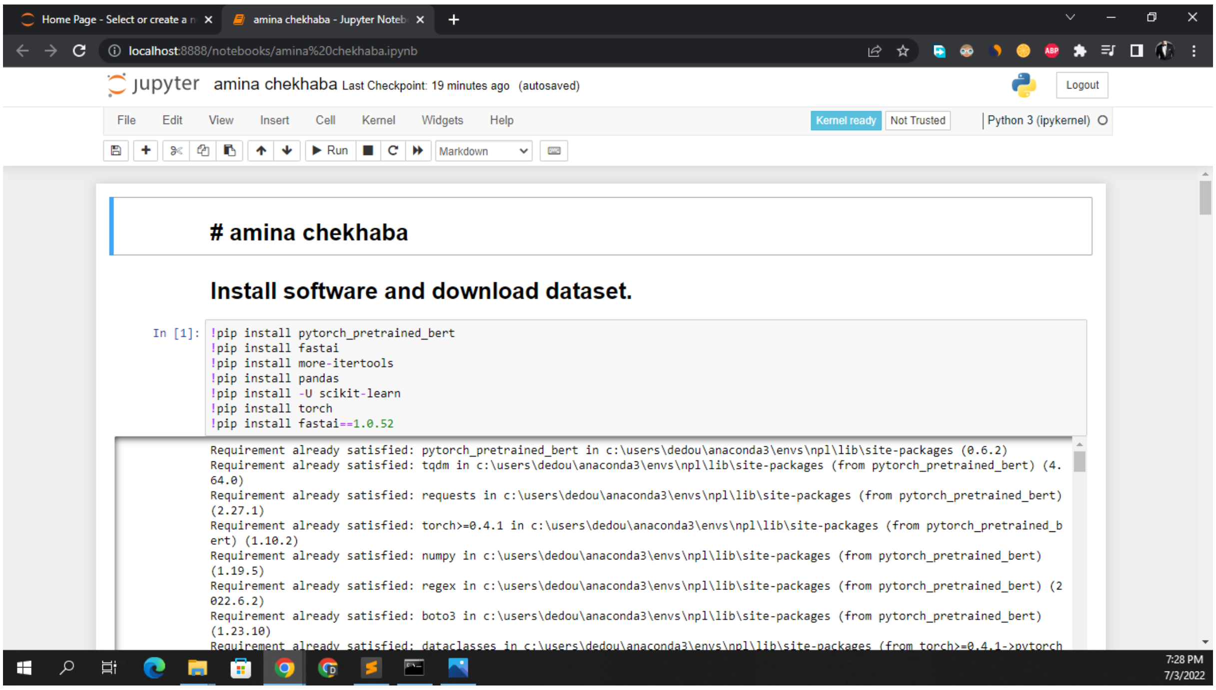

Fig. 22: Step 1 execute command link to install libraries In[1]

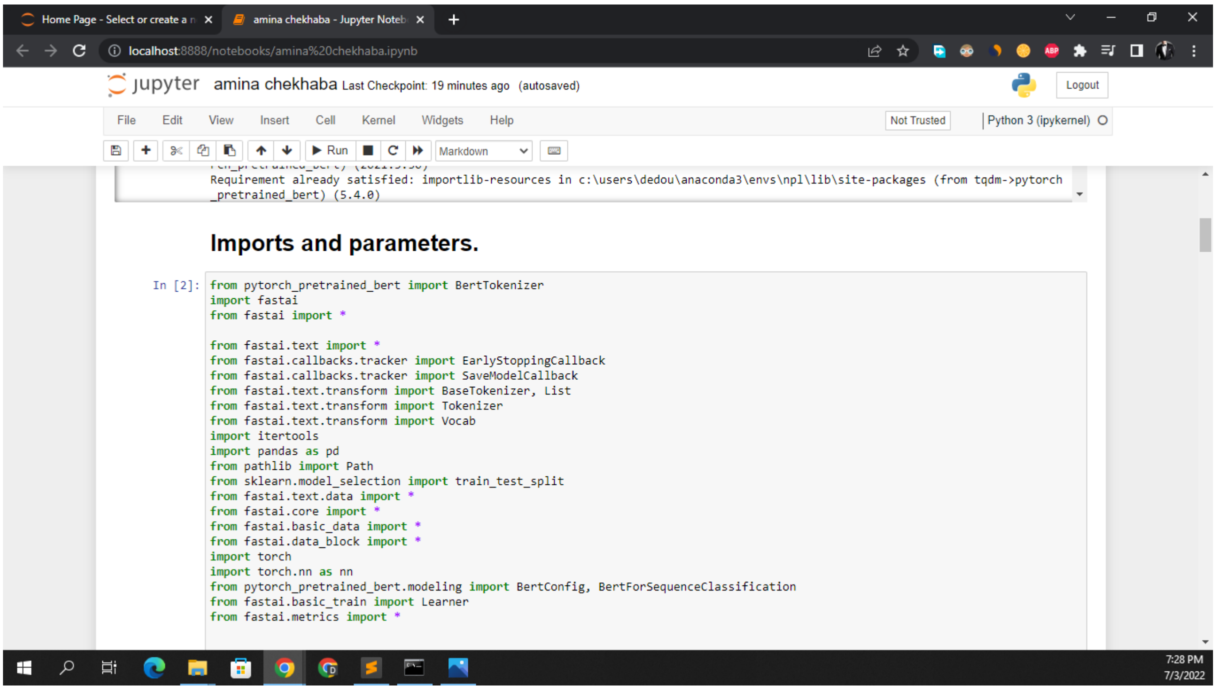

Fig. 23: Step 2 import libraries in Jupyter

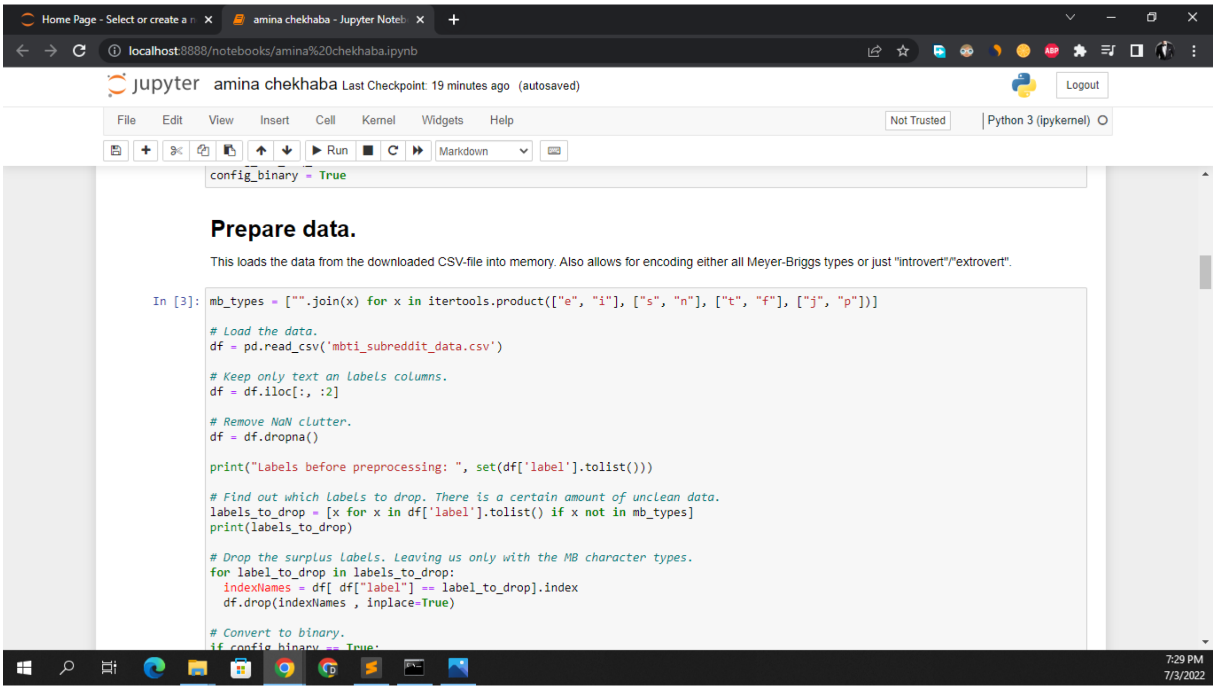

Fig. 24: Step 3 Prepare data In[3] (1)

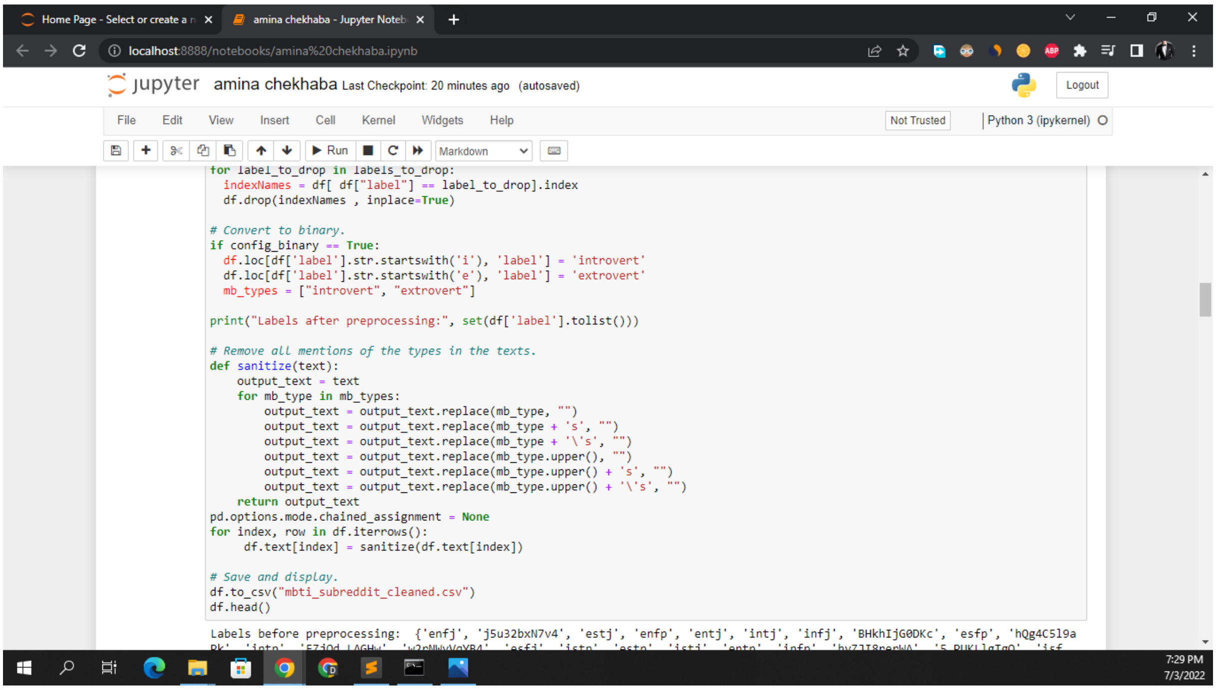

Fig. 25: Step 3 Prepare data (2)

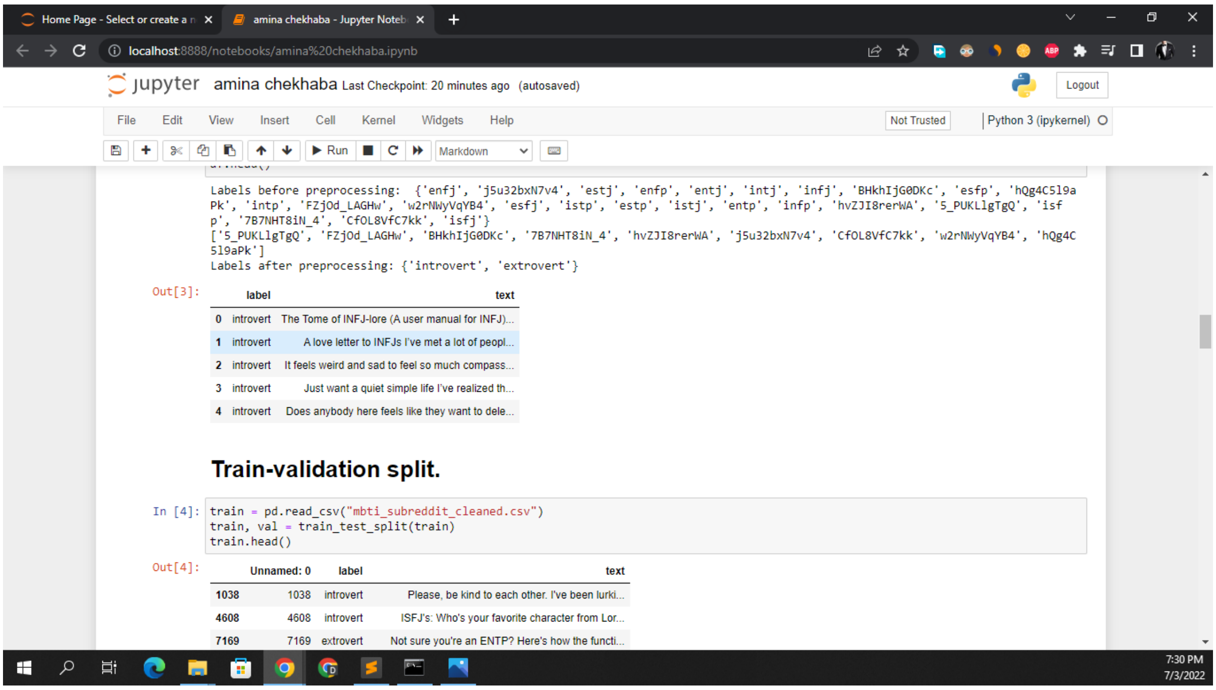

Fig. 26: Step 5 split data, validate data, train using data In[4]

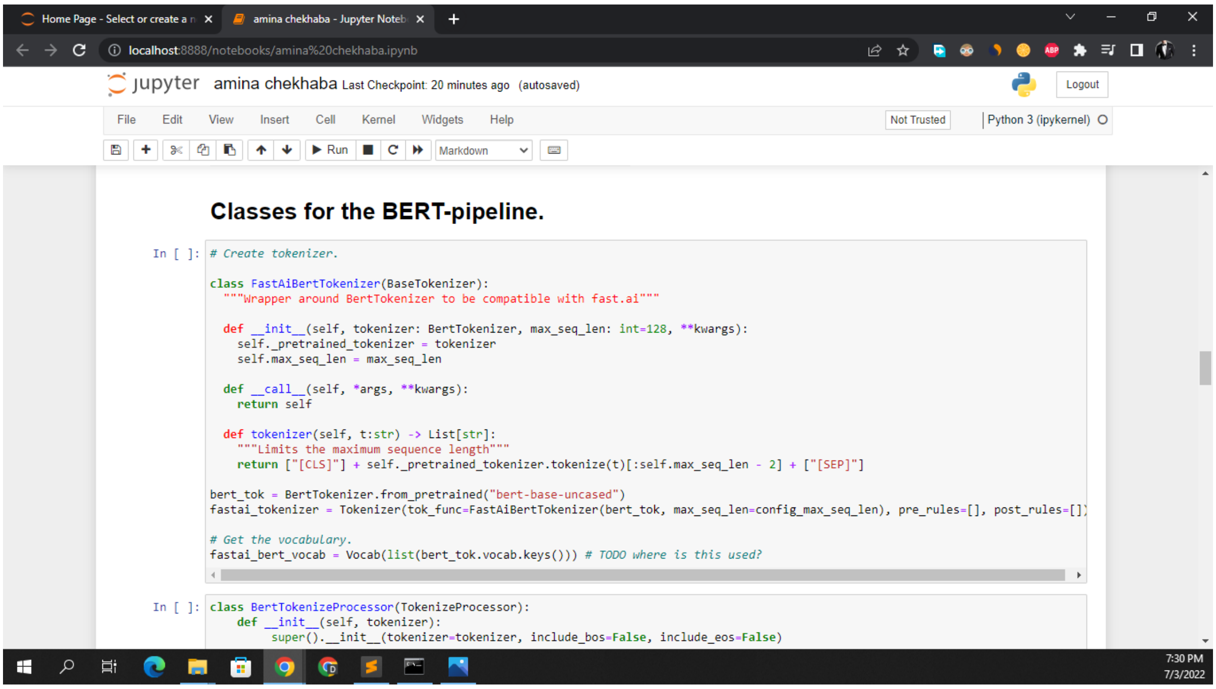

Fig. 27: Step 6 Classes for the BERT-pipeline (1)

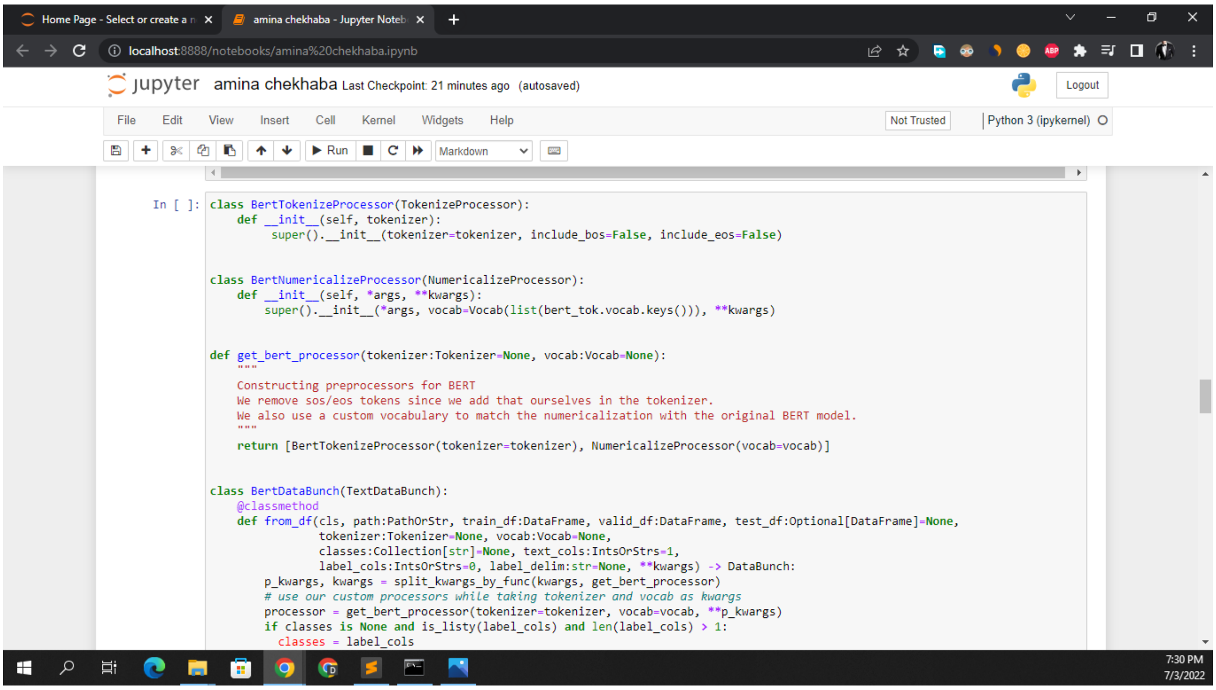

Fig. 28: Step 7 Classes for the BERT-pipeline (2)

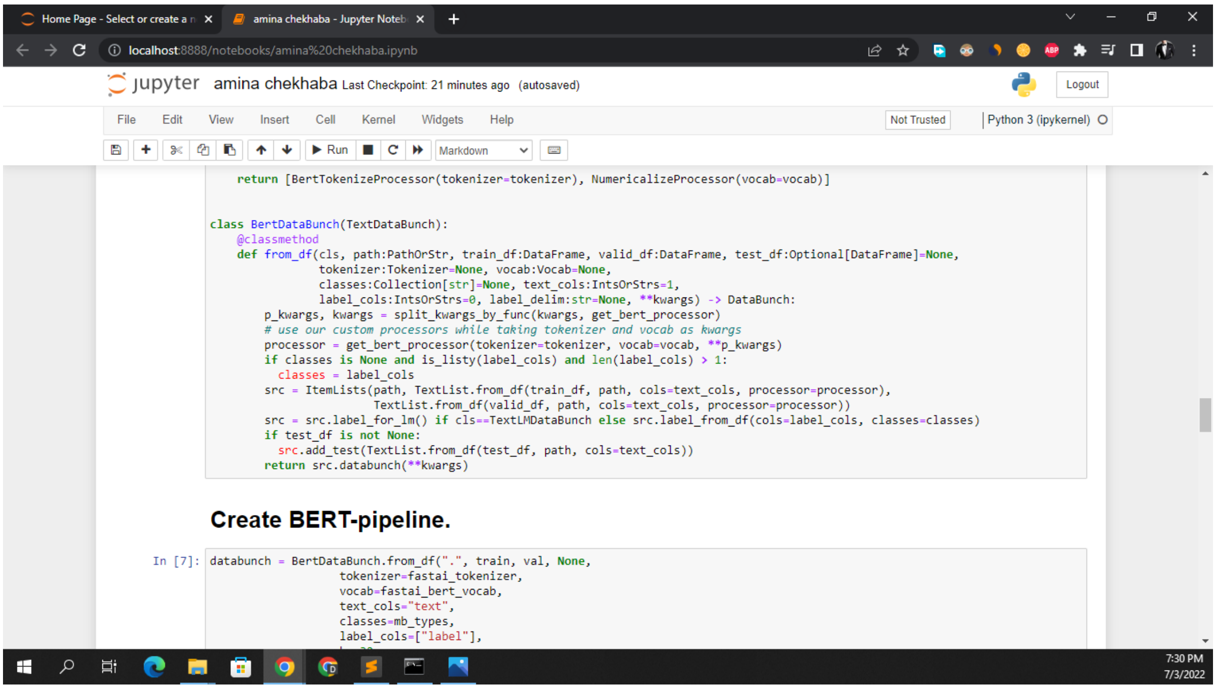

Fig. 29: Step 8 BERT-pipeline create branch of data to train model (1)

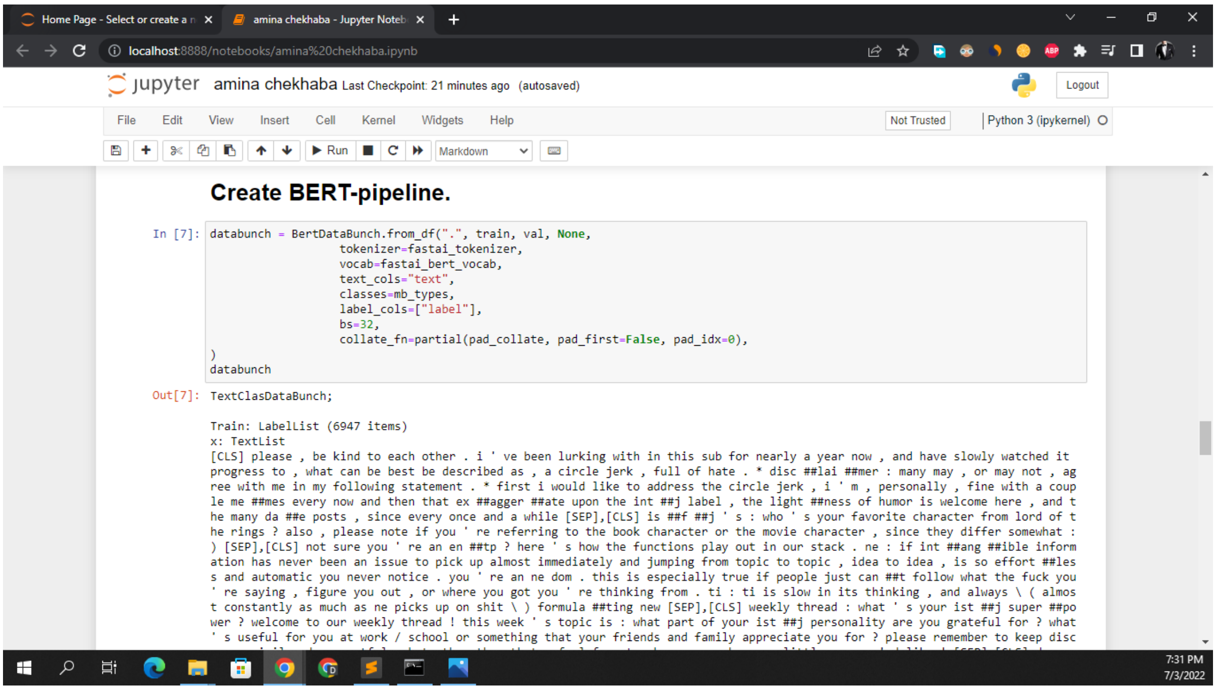

Fig. 30: Step 9 BERT-pipeline create branch of data to train model (2)

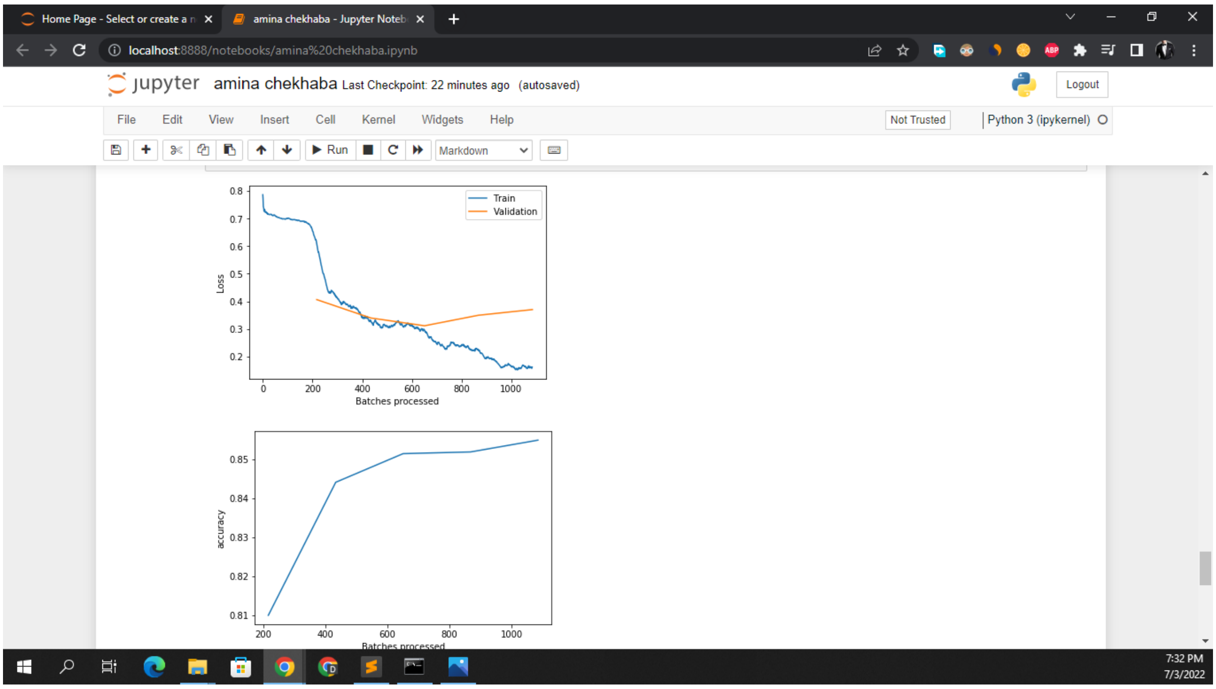

Fig. 31: Step 12 Graphs Machine Learning and accuracy results

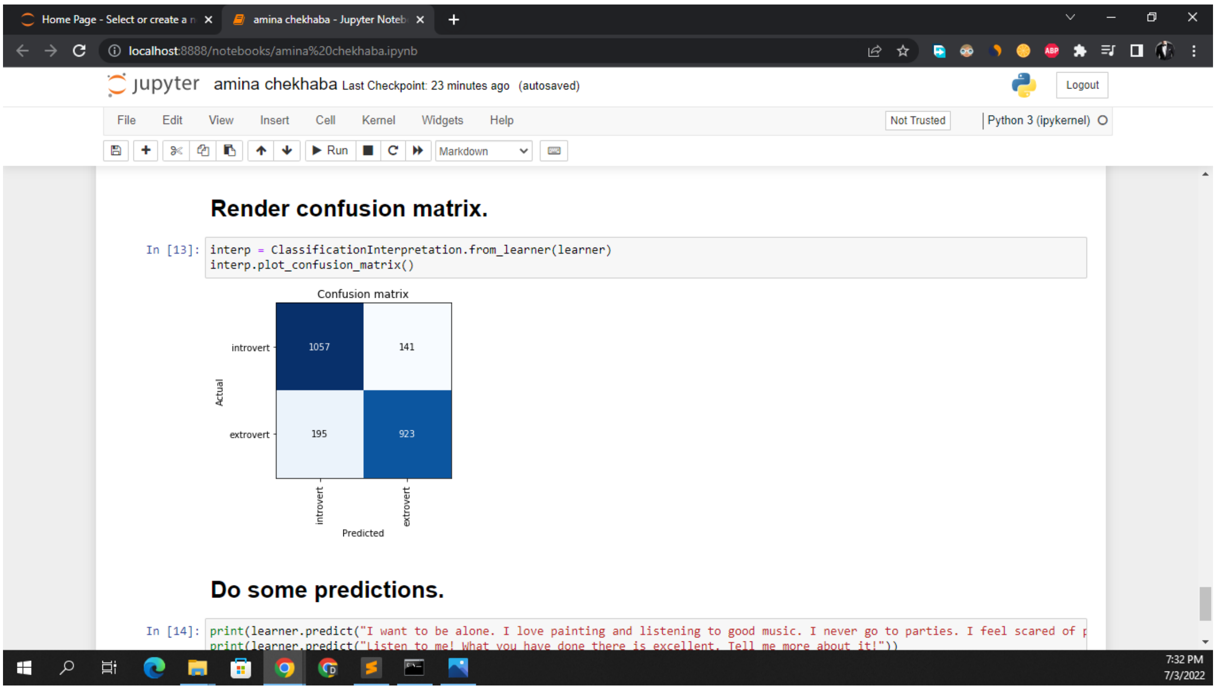

Fig. 32: Step 13 Classification Matrix

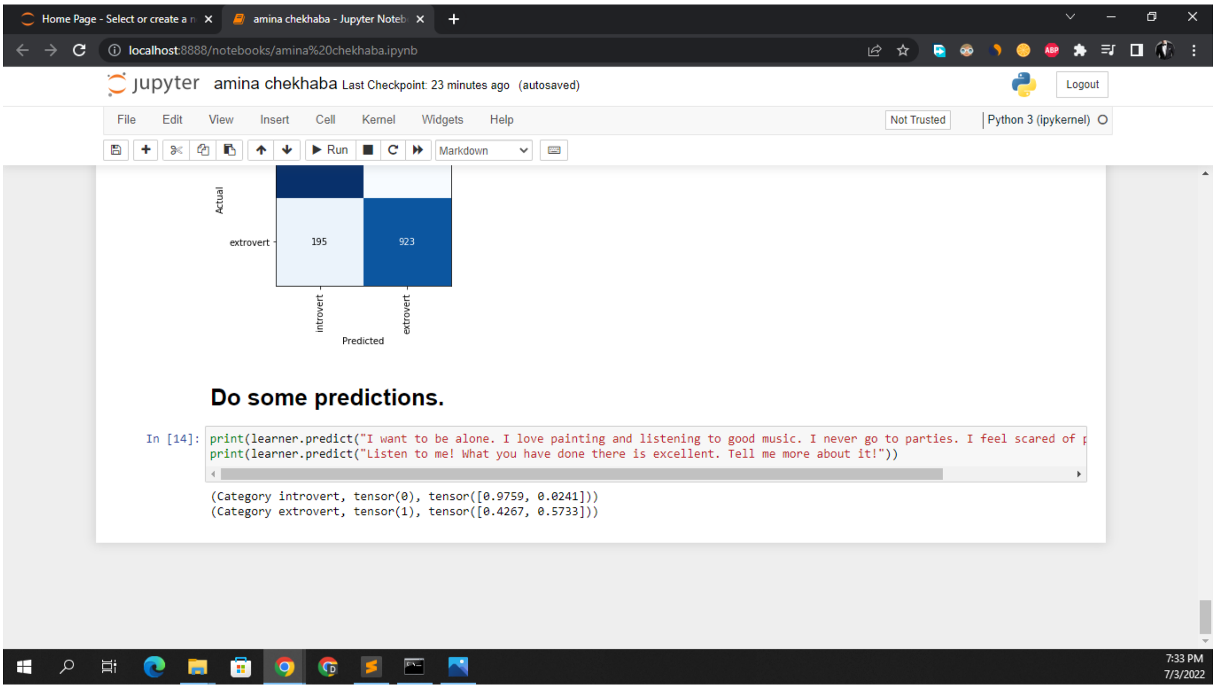

Fig. 33: Step 14 Results with two examples

Conclusion

In conclusion, this app takes an input of text and in return types the individual by classifying emotions using NLP and deep learning.

This study was able to predict personality utilizing social network data with a machine learning algorithm that we applied.

Also, the “Recurrent Neutral Networks” machine learning algorithm is the best model for predicting personality based on “MBTI”. Companies would substantially benefit from this since they would be able to study their candidates’ social network profiles before choosing suitable employees.

CONCLUSION

Due to the fast evolution of computer science and the wide use of machine learning in the health industry, we put mental health diagnoses under the microscope.

In summary, this study was able to predict personality from social network data using a machine learning algorithm that we applied. For comparison, we chose to use the Recurrent Neutral Networks machine learning algorithm as our personality type prediction model based on Myers-Briggs MBTI.

Companies should make a significant profit by using it in their recruitment and training programs. Since they would be able to study their candidates' profiles on social networks before selecting suitable employees.

The limitation of the Myers-Briggs type indicator from the text is only the first level in developing a personality type model. The only social network used for this project was the Personality Cafe forum due to that deep learning is more accurate and effective with a large amount of data. Our data set is around 69K of lines in .csv spreadsheet [Personality Cafe]

Other social networks can provide useful data, which can improve the prediction model. When building teams to develop new software, play sports or fight crime, a technical position is one of the most important factors to consider when joining a team [30].

In addition, people's soft skills, such as mindset and personality, as well as their living environment must be considered.

From our internship supervisors and through research, we found that a successful diagnosis of mental health disorder is achievable using personality type correlations from a cluster of text inputs by classifying the emotions corresponding to one out of 16 personality Myers-Briggs types.

Each MBTI type has 32 variations which got a cluster of common words and emotional expressions [Dave & Shannon OPS System for MBTI]. It has shown that it is highly successful at typing people and controlling subjects using their savior functions natural and automatic responsibilities to certain behaviors. We were able to correlate those behaviors with certain mental health symptoms and disorders. For example, introverts tend to socially isolate themselves and thus have a higher risk of depression.

We tested the application with two tests:

- Test 1: input text “I want to be alone. I love painting and listening to good music. I never go to parties. I feel scared of people all the time.”
- Test 2: input text “Listen to me! What you have done there is excellent. Tell me more about it!”

After processing we got these results through analyzing the user type of personality in MBTI. The first result is introvert and the second one is extrovert and it does that for all the other binary letters type processing.

We collected text inputs from social networks and divided the dataset into MBTI types where each has its cluster of emotion classifications and after validating to be used for training the application. The app analyzes the submitted text using NLP and compares them to our data set, returning an MBTI binary typing result (model).

We used the latest and most popular programming language for intelligent algorithms Python in Windows. We also used Anaconda for ease of use to create an environment, Jupyter Notebook, Browser, and Unified Modelling Language (UML) to build and explain our application function. The libraries installed:

- “pytorch_pretrained_bert”;
- “fastai”;
- “more-intertools”;
- “pandas”;
- “-U scikit-learn”;
- “torch”;
- “fastai==1.0.52”.

Given the lack of time, we had to put some of our application models and ideas on hold for future work; we focused on the AI function that helps us diagnose individuals using BERT, fast.ai. , and Cross-Industry Standard Process for Data Mining (CRISP-DM).

For future work, we intend to use the Generative Pre-trained Transformer 3 (GPT-3), an autoregressive language model that uses deep learning to generate human-like text. [19] This work is only the beginning and remains open for several additions that we aspire to build in the future for this project. Among them:

- Therapy sessions booking and management system;
- Physical and mental health virtual records where the health professionals and their patients can access clear clustered data about their health history;
- Private and secure online communication between patients and therapists for less friction with the social stigma that only crazy people seek mental health services;
- Create an efficient option for therapists to ease and unify their report writing with a few clicks;
- The possibility of counseling services using Virtual Reality technology;
- Patients would be able to write reviews about their therapists for quality management of therapists on the platform;
- Add the option of extracting and sending official medical documents such as the COVID test certificate for any necessity like travel;
- Notify patients to take their medications and update their medical history.

RECOMMENDATIONS

- Implement the Virtual Health Record in health departments and educate the Algerian people about it via health and education institutions;
- Increase funding support for therapy research in Algeria and provide rooms with the appropriate instruments and equipment for every research process with proper control;
- Requirements for online and offline therapy electronic devices or software must be safeguarded in advance and regularly maintained;
- Providing rapid internet access on a national scale and distributing it to remote areas;
- At the university level, developing an active group to study and research the barriers to seeking therapy and conduct comparative studies on the needs for online therapy in Algeria and leading nations;
- Hold seminars and events at every academic level about the importance of therapy in the overall health of individuals;
- Implementing computer, Internet, and digital floor training courses for e-therapy.

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ABSTRACT

الملخص:

يمكن التعبير عن مصطلح "الشخصية" من حيث الفروق الفردية في خصائص وأنماط التفكير والشعور والسلوك. يقدم هذا العمل العديد من تقنيات التعلم الآلي بما في ذلك "Naive Bayes" و "Support Vector Machines" و "Recurrent Neural Networks" للتنبؤ بشخصيات الأشخاص من النص استنادًا إلى "مؤشر نوع Myers-Briggs (MBTI)".

علاوة على ذلك ، يطبق هذا المشروع "CRISP-DM" ، والتي تعني "العملية القياسية عبر الصناعة لاستخراج البيانات" ، لتوجيه عملية التعلم. نظرًا لأن "CRISP-DM" هو نوع من التطوير التكراري ، فقد اعتمدناه بمنهجية رشيقة ، وهي طريقة تطوير برمجيات تكرارية سريعة ، لتقليل دورة التطوير إلى الحد الأدنى.

الكلمات المفتاحية: الذكاء الاصطناعي؛ التعلم الالي؛ مؤشر نوع مايرز بريجز ؛ بيرت؛ التعلم العميق؛ اضطرابات الصحة النفسية.

Résumé:

Le terme « personnalité » peut être exprimé en termes de différences individuelles dans les caractéristiques et les schémas de pensée, de sentiment et de comportement. Ce travail présente plusieurs techniques d'apprentissage automatique, notamment "Naive Bayes", "Support Vector Machines" et "Recurrent Neural Networks" pour prédire la personnalité des personnes à partir d'un texte basé sur "Myers-Briggs Type Indicator (MBTI)".

De plus, ce projet applique « CRISP-DM », qui signifie « Cross-Industry Standard Process for Data Mining », pour guider le processus d'apprentissage. Étant donné que "CRISP-DM" est une sorte de développement itératif, nous l'avons adopté avec une méthodologie agile, qui est une méthode de développement logiciel itérative rapide, pour réduire au minimum le cycle de développement.

Mots clés : IA ; Le Machine Learning ; ANN ; Myers-Briggs ; typage de la personnalité MBTI ; BRET ; Le Deep Learning ; Troubles de santé mentale.

Abstract:

The term personality can be expressed in terms of individual differences in characteristics and patterns of thinking, feeling, and behaving. This work introduces various machine learning techniques, including Naive Bayes, Support Vector Machines, and Recurrent Neural Networks, to predict people's personality from text based on the Myers-Briggs Type Indicator (MBTI).

Additionally, this project applies CRISP-DM, which stands for Cross-Industry Standard Process for Data Mining, to guide the learning process. Since CRISP-DM is a type of iterative development, we introduced it with an agile methodology, which is a rapid iterative software development method, to reduce the development cycle to a minimum.

Keywords: AI; Machine Learning; ANN; Myers-Briggs; MBTI Personality Typing; BERT; Deep Learning; Mental Health Disorders.