

## ORIGINAL RESEARCH ARTICLE

# En-route for an Automatic early stress & non-stress detection analysis for supervised learning with Bayes' theorem based on multimodal measurements

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## ABSTRACT

Chronic stress leads to mental health issues as well as other physical health issues such as cardiovascular disease. Excessive use of social media leads to Psychological stress. Around 20% of the world's, among those aged 15 to 29, children and adolescents agonize from psychological illness through suicide is the second largest reason for impermanence. Mental Health Conditions may have a substantial effect on all aspects of life such as work performance or school, family and friend relationships, and socializing in society. A state of total well-being is one in which the mind is at ease and the body is upright. While much research has been done to determine the mind-body connection, a recent study found that heart health is strongly related to mental wellness. In a recent statement issued in the journal Circulation by the American Heart Association on March 9th, 2021, it was established that good psychological health can minimize the risk of heart disease. Today's challenge is Covid 19 pandemic which caused anxiety, loneliness, fear of the pandemic, being infected, pessimism, etc. are the causes of major Heart diseases. People have turned to the Internet for help due to the lack of access to face-to-face management. The critical need for dependable and effective digital solutions is highlighted and designated by many available and widely accessible. We have proposed the framework for identifying the values of stress words and non-stress words using the Bayes theorem formula. If the words are stress words, then an action plan can be formulated thereby reducing the suicides and assuring the well-being of individuals. Finally, precision and accuracy are achieved with ISDF (Improved Stress Detection Framework) and Stress Detection using Bayes Theorem, unlike TensiStrength.

**Keywords:** chronic stress; cardiovascular disease; American heart association; machine learning; data mining; social media; psychological health; Covid-19; Bayes' Theorem

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## 1. Introduction

Mental illnesses, in the contemporary decade, are on the increase all about 13% everywhere throughout the world. This issue of mental diseases now accounts for one out of every five years consumed deactivated due to post-conflict environments. The world's children and youngsters are suffering from mental illness near around 20%, with suicide being the second principal cause of impermanence. These concerns can have a substantial impression on all the characteristics of life, which includes work or school performances. It can be elaborated up to community participation and the relationships with family and

friends. The two of the utmost common mental health illnesses cause a cost to the global economy of about billions of dollars<sup>[1]</sup>.

Automatic early stress and non-stress detection analysis is a valuable application of machine learning that can assist in identifying and managing stress levels in individuals<sup>[2]</sup>. This technology can help to detect early signs of stress before it becomes severe, allowing for preventative measures to be taken. The analysis is performed using supervised learning techniques and is based on Bayes' theorem<sup>[3]</sup>. In this case, the algorithm is trained on data that is labelled as either stress or non-stress to learn patterns and make predictions about future stress levels<sup>[4]</sup>. The proposed algorithms for stress detection analysis have the potential to improve mental health and well-being by identifying stress early and providing appropriate support and interventions<sup>[5]</sup>. This can be especially useful for individuals who are prone to stress-related disorders or who work in high-stress environments<sup>[6]</sup>.

The extreme practice of social media leads to numerous mental health issues such as stress. Psychological health can be defined as an individual's or a group's entire emotional and psychological well-being<sup>[7]</sup>. A person's thinking, feelings, and behaviour are all influenced by their mental health. It is a necessary component of living a happy and healthy life. Many of us deal with mental health issues regularly<sup>[8]</sup>. When a mental health issue becomes chronic and begins to interfere with one's capacity to live a normal life, it may be a sign of an underlying mental disease<sup>[9]</sup>.

## 2. Literature analysis

A frequent but serious mental illness is depression. Additionally, 264 million individuals worldwide suffer from depression, according to the WHO<sup>[10]</sup>. Low self-esteem, feelings of hopelessness or unhappiness, and a lack of enjoyment in once-enjoyable activities are all signs of depression. Depression is distinct from frequent and transient mood changes. Emotional responses to happenings in daily life. Depression can be brought on by a variety of things, including persistently stressful life experiences, work pressure, personality disorders, family history, and giving birth<sup>[11]</sup>. When depression is persistently moderate or severe, it can lead to major health problems. In such a situation, depression may cause the person to have a severely low mood, be less productive at work or school, or even result in suicide<sup>[6]</sup>.

Nowadays, psychological stress is becoming a danger to people's health. Recognizing and managing stress before it develops into more serious problems is crucial<sup>[12]</sup>. Four different techniques make up Psychological Stress Detection (PSD), including psychological assessment, physiological signal evaluation, behavioural responses (Twitter), and visual and social media interactions (Facebook, WhatsApp)<sup>[13]</sup>. To predict the PSD from social media, particularly through SNS, we took into account textual behavioural reactions, visuals, and social media interactions in this work<sup>[14]</sup>.

Lin et al.<sup>[9]</sup> and colleagues identified psychosomatic stress in 2014 using language, image properties, and computation responses obtained through tweets<sup>[15]</sup>. The study further stretched on their work in 2017 by using CNN and FGM approaches to raise the stress exposure rate in tweets n between 87.2% and 91.4%. The tweets for the analysis of stress<sup>[16]</sup> include social interaction attributes, text, visuals, and behaviour, as well as the behaviour serving as an additional attribute<sup>[17]</sup>.

Research attention on identifying psychological stress in SNS is rare<sup>[18]</sup>. Due to numerous young children committing suicide while using social networks, the "blue whale challenge game" horrified the entire world<sup>[19]</sup>. According to reports, the "Blue Whale Challenge" is an online "suicide game" that assigns 50 tasks spread over 50 days to youths. Many deaths worldwide were allegedly connected to the challenge<sup>[20]</sup>. Rina Palenkova is credited with starting the Blue Whale challenge. In a particular kind of chat room run by VKontakte, the biggest social network in Russia, there was a discussion on Rina Palenkova's passing<sup>[21]</sup>. Teens would congregate in these forums to discuss lighter topics, including despair, loneliness, and suicide, as well as more

serious ones, like school and which classmates they liked<sup>[19]</sup>. However, the “game” was not as simple as it seemed<sup>[22]</sup>. It has been discovered that the players of stress-relieving games use suspicious activity-related terms inside their personal SNS profiles<sup>[23]</sup>. A large portion of these keywords relates to psychological stress levels. The decision to commit suicide is brought on by an increase in acute stress levels. The cybercrime agency must monitor these offenders’ microblogs for instigating suspicious behaviour on SNS before taking serious action to apprehend them<sup>[24]</sup>.

### 3. Proposed framework

In this Section, the operational phases of the Improved Stress Detection Framework (ISDF) for predicting the stress from SNS are elaborately illustrated in **Figure 1**. The Stress Detection (SD) algorithm initiates the steps to capture the short posts/microblogs that are sent between the clients/users and stores them in the database for identifying Stress using a Set of pre-defined logical rules (SPSWDB) shown in **Table 1**, and Ontology-based Information Extraction (OBIE) technique. The overall framework for Improved Stress Detection Framework is presented in Mohammad et al.<sup>[10]</sup>. To extract the pressure words from the archive, hybrid ontology is used<sup>[11]</sup>.

#### 3.1. Processing steps: ISDF framework

- 1) The First step is to capture the Short Posts and Microblog messages sent between the chat mates of the Social Networking Site (SNS). These messages are saved in the Microblogs database (MDB).
- 2) In this Second step, Text posts are taken, and these text messages are Segregated into plain text by removing stop-words (prepositions, articles) and emoticons.
- 3) The third step consists of Three (3) important tasks for the detection of stress are given below (refer to **Table 1**):
- 4) Each of the Textual keywords of the plain text is picked and compared with pre-defined logical words defined in SPSWDB (Rule 1) to find out the linguistic lexicon of stress words (Stress Lexicon, Negative emotion Lexicon, and Negating Words Lexicon) present in the Text. During this process, WordNet Hybrid Ontology is effectively utilized if a mismatch occurs.
- 5) The Values calculated from the above steps are stored in TTDB (Text trends database).
- 6) The stress words that are compared with SPSWDB (Set of Predefined stress words database) on detection are shortlisted and then stored in KSDB (Knowledge DB) Subsequently, Emoticons for which a match is found after comparing with SPSWDB are also stored in KSDB.
- 7) Similarly, the calculated Mean value of social interactions i.e., likes and comments are checked with the pre-defined threshold value if it is met then that value is stored in KSDB.
- 8) All the features retrieved from the Textual attribute, Emoticons attribute, Image, and Social interaction attribute which is stored in KSDB are fed into the probabilistic Stress Detection algorithm to predict the stress levels of the user.
- 9) Finally, in the last step results obtained regarding stress levels and their seriousness are predicted, which is stored in the form of the report. If the chatting session activities encounter stressful activities, then a recommendation is submitted automatically to the e-crime department for appropriate action for stress management in Social Networking Sites.
- 10) We used different database tables namely MDB, TTDB, EMDB (Email and Mobile database), ODB, SPSWDB, SKDB, EMDB, and Metadata. In this Framework, (the Short Posts database) is used to store the online messages/posts that are communicated between the users (chatmates). ODB (Ontology Database) is a lexical database that identifies terms, Synonyms, Concepts, Taxonomy (concept hierarchy), relations, Axioms, and Rules<sup>[25]</sup>. The OBIE is a probabilistic learning process that identifies the domain to which these stress words belong. The proposed framework can be combined with other instant

messengers and community networking sites such as MSN, Instagram, WhatsApp, Twitter, Facebook, Yahoo, Skype, GTalk, etc.<sup>[14]</sup>.

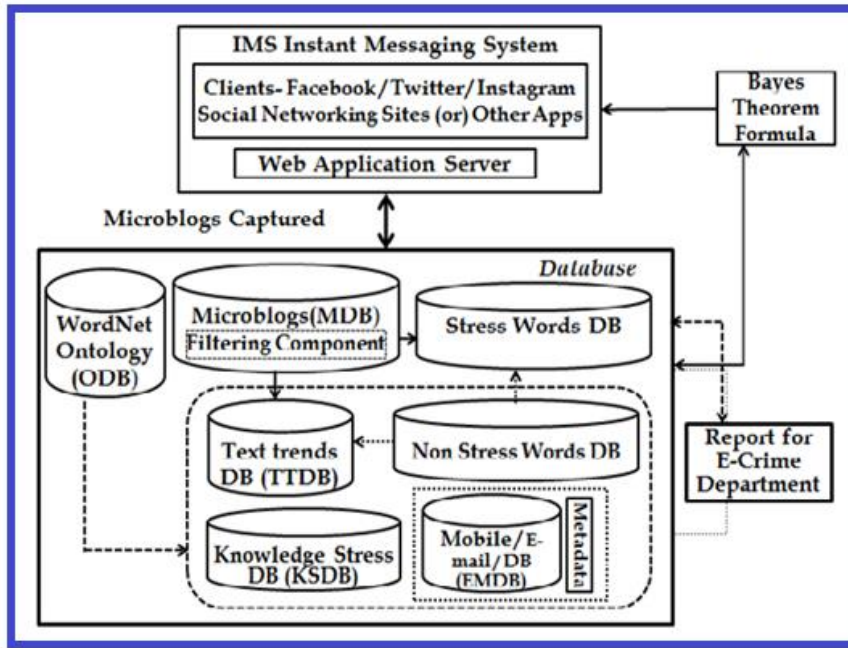



Figure 1. Proposed stress detection framework.

Table 1. Set of knowledge-based pre-defined logical rules internally supported with wordnet ontology for rule 1 linguistic stress lexicon words (SPSWDB).

<b>RULE 1 (SPSWDB)</b>	
<b>Categories of Stresses (Domain)</b>	<b>Stress words/Emoticons or Images to be detected</b>
Stress Lexicon →	Anxious, sad, depressed, anger, pain, grief, restless, sleepless, failure, sorrow, lonely, quit, worry, nervous, mental, break, anguish, argue, arrogance, atrocious, bereave, brokenhearted
Negative emotion Lexicon →	Hurt, ugly, anger, annoy, boredom, sadness, grief, disapproval, low self-esteem, callous, despair, devastate, hate
Negating words Lexicon →	Cannot, can't, couldn't, could not, didn't, did not, doesn't, does not, don't, do not, hasn't, have not, isn't, is not, never, no, not, shouldn't, should not, won't, won't, wouldn't
Emoticons and Images → (Mean Value)	“%-( “, “)-:”, “):”, “) o:”, “:( “, “: *(“ , “: (“, “:-”, “:-&”, “:- (“, 
<b>RULE 2 (threshold value)</b>	
Check the user-defined threshold value for the stem words that may belong to multiple domains, using precision and Mean values (Rule 1 and Rule 2) <b>SD algorithm</b>	
<b>RULE3 (undetected words to be ignored)</b>	
Sometimes, Special characters and unknown image formats are also sent via SNS which are ignored	

### 3.2. Classification using Naïve Bayes classifier

A mathematical formula that helps us to appraise the probability of an event is Bayes' theorem. It states that the probability of a hypothesis (H) with some specified observed evidence (E) is equivalent to the prior probability of the hypothesis (P(H)), multiplied by the probability of observing the evidence given the hypothesis (P(E|H)), divided by the probability of observing the evidence overall (P(E)):

$$P(H|E) = P(H) \times P(E|H) / P(E)$$

where:

The probability of the hypothesis  $P(H|E)$  gives the evidence (also known as the posterior possibility).  $P(H)$  is the prior probability of the hypothesis (i.e., our initial belief in the absence of evidence). For observing the evidence  $P(E|H)$  is the likelihood that gives the hypothesis (i.e., how well the hypothesis explains the suggestions).  $P(E)$  is the likelihood of observing the evidence overall (also known as the marginal likelihood).

In essence, Bayes' theorem tells us how to modernize our belief in a suggestion based on new evidence. By incorporating the possibility of the evidence given the assumption, we can revise our probability estimates and arrive at a more accurate assessment of the probability of the hypothesis.

### 3.3. Topic (Domain) Hierarchy Construction GSHL algorithm

Wei et al.<sup>[26]</sup> had proposed Global Similarity Hierarchy Learning (GSHL), This algorithm recursively searches for the most similar topics of the current "root" topic and removal those that do not satisfy the condition on the difference of  $K_L$  divergence. Both algorithms start with an initial topic as the root node and look for the top and most similar topics according to (*dis*)similarity measures. The parameters used in the Algorithm 1–3 are as follows,

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#### Algorithm 1 GSHL (root)

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```

1: Require Initialize  $V, M_s, I, TH_s, TH_d, TH_n$ , and  $M_c$ .
2: Ensures: A terminological ontology with "broader" and "related" relations.
3: Initialize  $V, M_s, I, TH_s, TH_d, TH_n$ , and  $M_c$ ;
4: while ( $i < I$  and  $V$  is not empty) do
5:   Add current root into  $V$ ;
6:   Select the most similar  $M_c$  nodes (words) of
7:     root word (topic) from  $M_s$ ;
8:   Add similar nodes into  $V_{temp}$ ;
9:   Remove nodes in  $V_{temp}$  against//similarity and divergence //difference condition
10:  for (all nodes  $n$ , in  $V_{temp}$ ) do
11:    if ( $\text{Sim}(n_i, \text{root}) > \text{Sim}(n_i, \text{Sibling}(\text{root}))$ ) then
12:      Assert broader relations between root and
13:      topic  $n_i$ ; //relationship between topics is broader
14:    else default
15:      Assert related relation between root and
16:      topic  $n_i$ ; //relationship between topics is nearer
17:    end if
18:    Move topic  $n_i$  from  $V_{temp}$  to  $V$ ;
19:    Increment  $i$  by 1;
20:  end for
21:  Remove current root from  $V$ ;
22: end while

```

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#### Algorithm 2 *TreeAlignment* (*RootNode, node*) for Domain (Topic) extraction using Ontology concepts

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```

1: Require: Initialize RootNode, Node(s) and MinThreshold value
2: Ensures: Domain i.e. topic extraction from stress words.
3: for (int  $i$ :1 to numDomainTopic {
4: //traverse tree for DomainTopic  $i$ 
5: NumLevels=2; //size of tree is 2(parent & child)
6: for (int  $j$ :1 to NumLevels){
7:   RootNode[ ]Nodes=Empty // top most level 1
8:   Node[ ]nodes=getNodesAtlevel(nodes);
9:   //All the stem words from the TCDB at level 2
10:  RootNode[ ]Nodes=Node[ ]nodes
11:  //stem words assigned to RootNode
12:  checkForRepetitiveData(Nodes);
13:  { call Bayes(Root) } //check the stem words(TTDB)
14:  //matched in other domains i.e. SPSWDB using Ontology
15:  checkFordisjunctiveData (nodes);
16:  { call Bayes (Root, MinThreshold) } //check for stem
17:  //words that belong to more than one domain (topic)
18: } //end for
19: } //end for

```

---



SD algorithm is the backbone for the proposed Stress Detection Framework, as already discussed in the previous section that has initiated the overall progress starting from storing text messages in *SWDB* to finding the stress keywords by providing a detailed report from *KSDB* and *MDB* databases to E-crime department on detection of stress words.

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**Algorithm 3** Stress Detection Algorithm (SD)

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```

1: Input: Short posts/microblogs stored in Text Database (SWDB) (day to day) from instant messaging system: (IMS)/SD Framework.
2: Output: Report to E-crime when Stress messages are detected
3: Do{ //Apply Ontology-based IE technique for filtering unnecessary words and pick stress words from SWDB (if found) and push to
    //(TTDB) for Text and (EMDB) emojis which
    //include stem words mapped with pre-defined
    //knowledge-based rules stored in (SPSWDB) rule 1 & rule
    //discussed in section 3.
    Push Messages to SWDB //instant messages stored in SWDB
4:   Do { //Scan SWDB for relevant stress word patterns if found
        //store it in TTDB and perform mapping with SPSWDB
        //(rule 1) using
        // Ontology (OBIE) building taxonomy of stem words
5:     Call TreeAlignment algorithm { // algorithm discussed in Tree Alignment Algorithm
        // initially all stem words (TTDB) mapped to empty root
        //node using OBIE model forming tree
6:     Call Naïve Bayes Classifier
7:     Call GSHL algorithm { //Check threshold values of stem
        //words (TTDB) with root nodes stored in SPSWDB (rule 1) using
        //algorithm 1 shown in GSHL Algorithm and finds stress type(s) activity i.e. domain topic(s)
8:       Scan TTDB
9:       Push patterns to KSDB //stem words
        } //end of call GSHL
10:      Compare TTDB with SPSWDB{
11:        If TTDB==SPSWDB Then Push patterns to KSDB
        //stem words with Stress Domain(s) stored
        else
        Do Nothing
12:        End If
        } //end compare
        } //end call TreeAlignment
13:      until TTDB!=NULL //end of do
14:      If TTDB==KSDB Then //Stress words found with Domain
15:      Check KSDB { //check the knowledge database using E-crime
        // monitoring system program for the type of cyber threat
        // activity (i.e stress linguistic stem words along with stress
        // category (i.e domain) using the Treealignment algorithm
16:        if KSDB=='TRUE' then { // if Stress words match then
17:          Check MDB { //trace the profile details (email, phone
        //number, ISP IP address, and location details
18:          Report to E-crime Department //detailed report
        //including threat activity details traced from KDB/MDB
19:          } //end of check MDB
20:        } //end if
21:      } //end of check KSDB
22:    } //end of do

```

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Overall working of our proposed Stress Detection Framework for identifying stress messages and reporting to the E-crime department.

## 4. Experimental results analysis

Various messages shared among the users of social media are gathered, and the scoring class of messages whether it is stressed or Non-stressed is identified with Bayes' Theorem Formula as shown above. The recall, and F1 score of the algorithm, are measures of its ability to correctly identify stress and non-stress states. The results can also provide information on the sensitivity and experimental results provide information on the accuracy, precision, and specificity of the algorithm, which are measures of its ability to correctly classify

positive and negative instances<sup>[21]</sup>. The below figures i.e. **Figures 2** and **3** depicts the analysis of stress and non-stress values of stress words.

```
String: 1.I feel tense, anxious or have nervous indigestion.
Dominant: stress, scores:
Array
(
  [stress] => 0.727
  [neu] => 0.182
  [non-stress] => 0.091
)
String: 2.I am in pain, can't take it anymore hate life depressed.
Dominant: stress, scores:
Array
(
  [stress] => 0.8
  [non-stress] => 0.1
  [neu] => 0.1
)
String: 3.i am anxious feeling intolarable today due to pandemic covid 19.
Dominant: neu, scores:
Array
(
  [neu] => 0.401
  [stress] => 0.4
  [non-stress] => 0.2
)
String: 4.Its my birthday I am so excited and delighted.
Dominant: non-stress, scores:
Array
(
  [non-stress] => 0.666
  [stress] => 0.167
  [neu] => 0.167
)
```

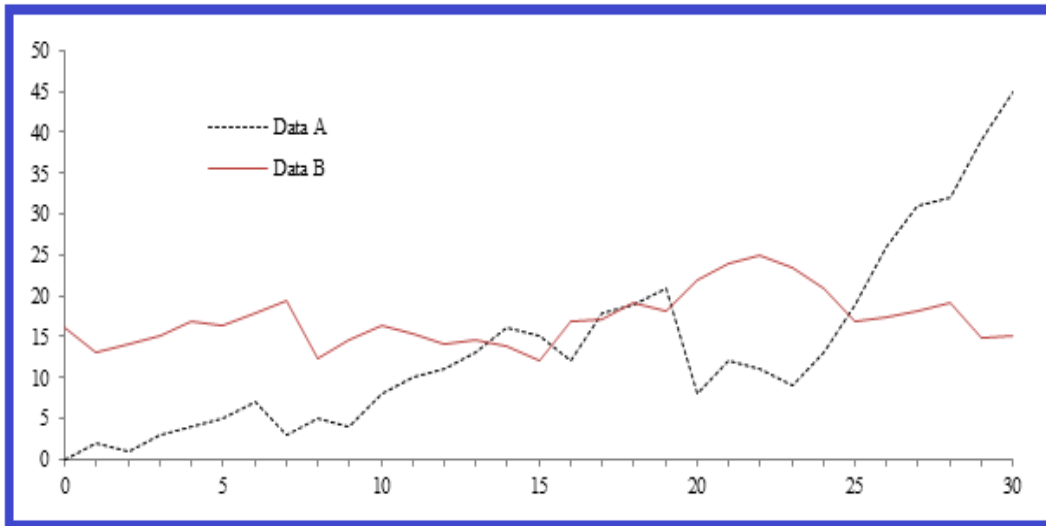
**Figure 2.** Experimental evaluation of stress and non-stress words.

```
String: 5.I am feeling Lonely
Dominant: neu, scores:
Array
(
  [neu] => 0.401
  [stress] => 0.4
  [non-stress] => 0.2
)
String: 6.Feeling Sad and Stressed because of pandemic
Dominant: stress, scores:
Array
(
  [stress] => 0.666
  [non-stress] => 0.167
  [neu] => 0.167
)
```

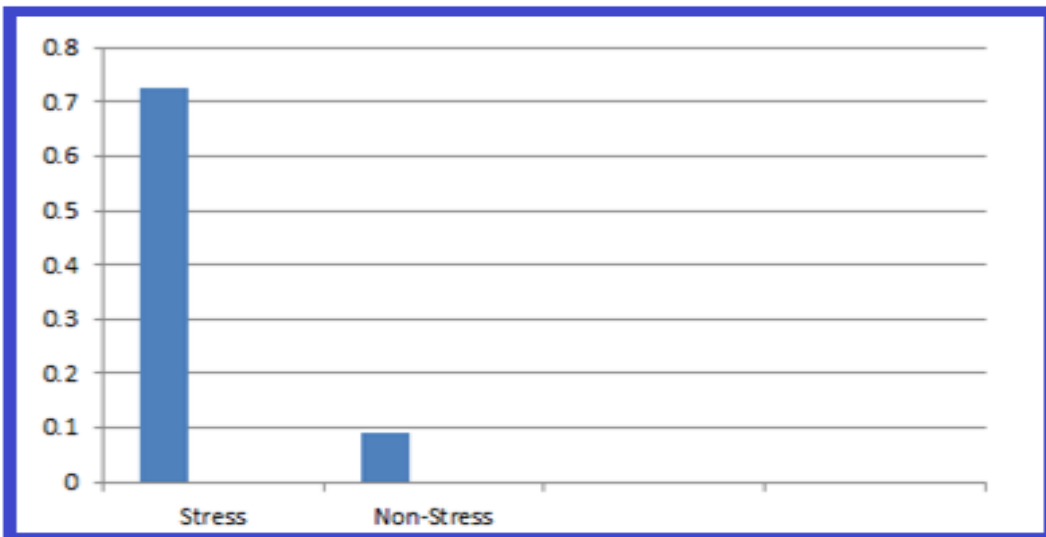
**Figure 3.** Experimental evaluation of stress and non-stress words.

Moreover, the experimental results can provide insights into the performance of the algorithm across different populations, such as gender, age, and cultural groups. This information can help to identify potential biases and improve the generalizability of the algorithm. The analysis of experimental results can also help to identify areas for improvement and refinement of the algorithm, such as the inclusion of additional features or the use of more advanced machine learning techniques. Additionally, the results can inform the development of personalized interventions to manage stress levels more effectively<sup>[22]</sup>.

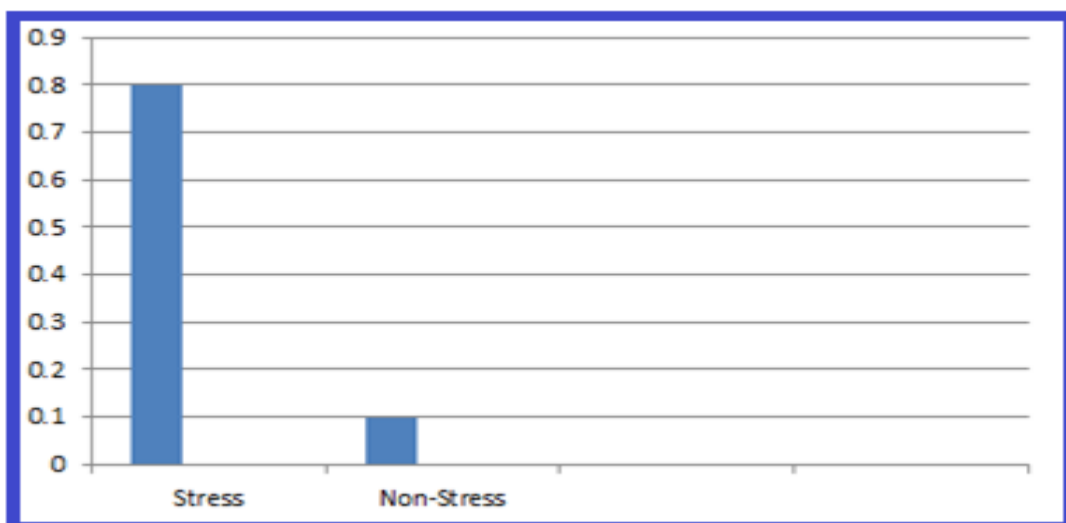
The analysis of experimental results is crucial in evaluating the effectiveness and potential of automatic early stress and non-stress detection analysis using supervised learning with Bayes' theorem and can provide valuable insights into improving mental health outcomes. The Figures depicted below i.e., from **Figure 4** to **Figure 10** are the visualization of experimental results as shown below.



**Figure 4.** Graph depicting the Extract posts on Twitter with numerous stressful confrontations (gloomy, sad).

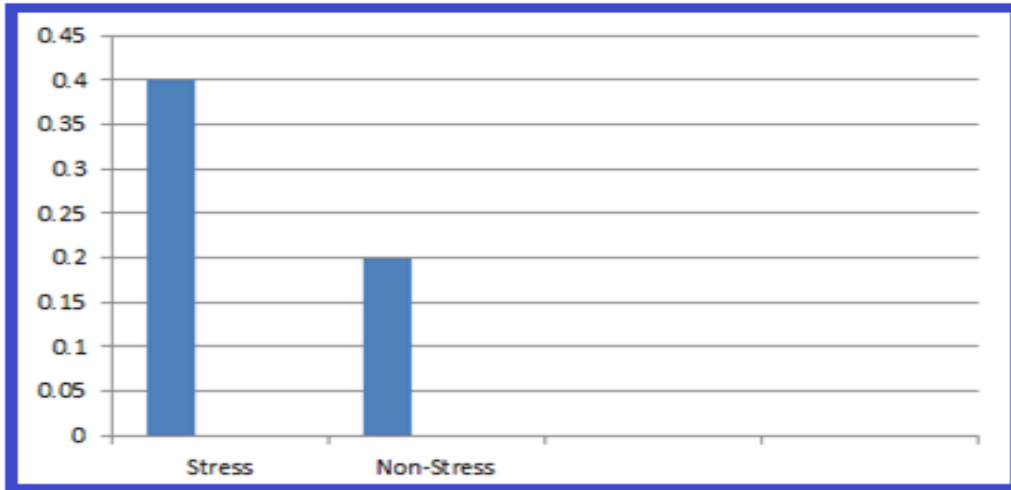


**Figure 5.** String1. My feeling is tense, nervous, or anxious Indigestion.

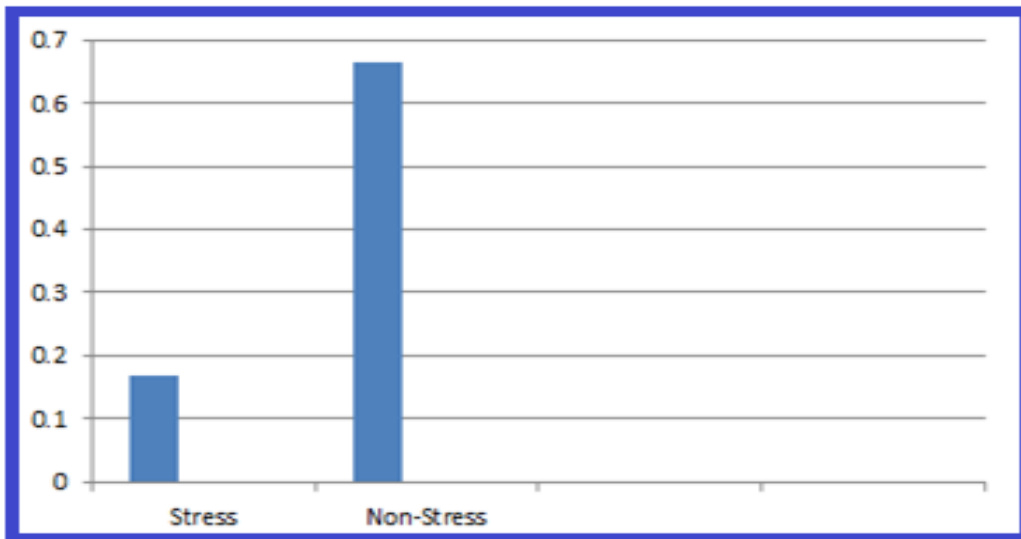


**Figure 6.** String: 2. I am in discomfort & can't take it any longer hatred life depressed.

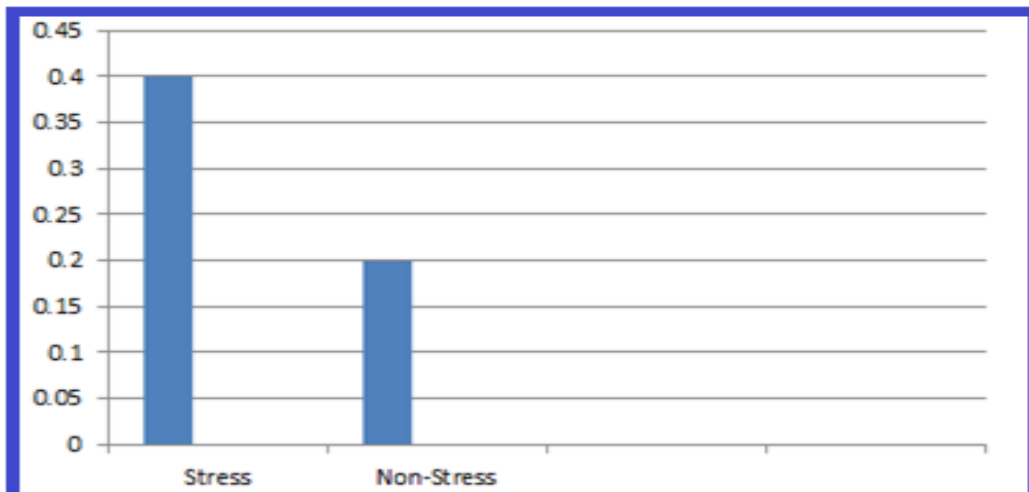




**Figure 7.** String: 3. I am anxious and feeling intolerable today due to the pandemic covid-19.



**Figure 8.** String: 4. it's my birthday I am so excited and delighted.



**Figure 9.** String: 5. I am feeling lonely.

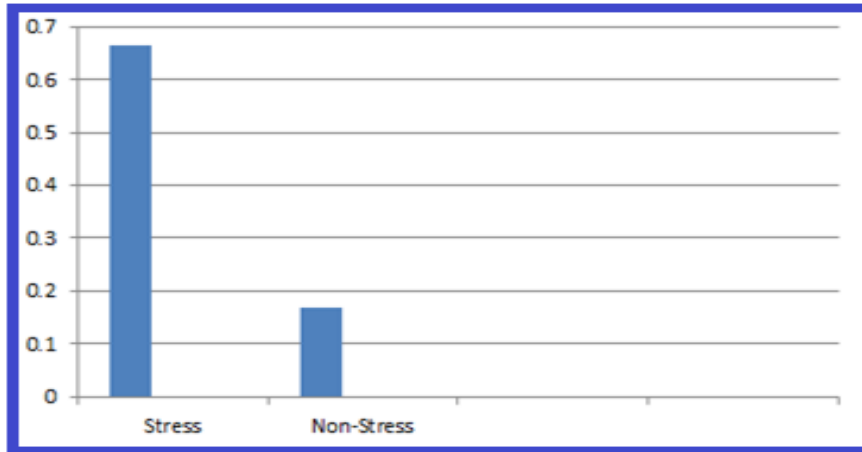


Figure 10. String: 6. Feeling sad and stressed because of the pandemic.

#### 4.1. Tested using ISDF Framework, TensiStrength, and Bayes Theorem

The real chatting session is intentionally conducted and the experimental results are demonstrated for the conversation that happened between the two users, as shown in **Figure 11**.



Figure 11. Real Tweet, consists of Linguistic stress lexicon words, emoticons, and image.

The Twitter chatting session (**Figure 11**), is tested using the ISDF Framework (**Figure 1**) and Bayes Theorem. The stress words in red-colour are detected namely “*unfinished work*”, and “*feeling stress*”. Apart from that, Emoticon which is exactly mapped with our pre-defined database (SPSWDB) *rule 2*, is 4. The precision rate obtained by Tensistrength is 58.32%, whereas 94.2% with ISDF and 62% with Bayes Theorem as shown in **Table 2**. The features of previous stress detection method and the proposed method is depicted in **Table 3**. Finally, precision and accuracy are achieved with ISDF and Bayes Theorem, unlike TensiStrength.

Table 2. The precision rate obtained for a real sample Twitter chatting session (**Figure 11**).

Parameters used	TensiStrength	ISDF system	Bayes Theorem
Textual data	98.11%,	94.43%	80%
Textual Emoticons	68.53%	96.21%	75%
Textual+Emoticons+Social Interactions	58.32%	94.20%	62%
Textual+ Social Interactions	97.49%	97.82%	97.25%

Table 3. Features of Tensistrength, ISDF System, and Bayes Theorem.

Features	TensiStrength	ISDF system	Bayes Theorem
Support for Social Interaction	Supported	Supported	Supported
Pre-Defined rules	Very less	More (because of WordNet)	More (because of WordNet)
Support for Emoticons and Images	Not Supported	Supported	Supported

**Table 3.** (Continued).

Features	TensiStrength	ISDF system	Bayes Theorem
Stress Activity Detection	Static Detection (time consumed is less)	Dynamic Detection (time consumed is more)	Dynamic Detection (time consumed is more)
Report Generation for e-crime department	No Report	Report with details (email, Mobile No, etc.)	Report with details (email, Mobile No, etc.)
Ontology support	No	Yes	Yes
Accuracy	No	Good	Good

## 5. Conclusion and scope of the work

### 5.1. Conclusion

Previous stress detection and prevention approaches such as interviews, surveys, etc. are identically inefficient and hysteretic. The happiness of society as well as individual's desires to detect and manage stress before develops a problem for civilization. Automatic early stress and non-stress detection analysis using supervised learning with Bayes' theorem is a promising technology for identifying and managing stress levels in individuals. The scope of automatic early stress and non-stress detection analysis is promising, with the potential to improve mental health outcomes for individuals and society as a whole. The technology can be extended to detect other mental health circumstances such as unhappiness and nervousness, allowing for earlier interventions and better outcomes.

By detecting early signs of stress and providing appropriate interventions, this technology can improve mental health and well-being. It has potential applications in various fields, including healthcare, education, and workplaces. With further development and refinement, this technology can make a significant impact on reducing the burden of stress-related disorders and promoting a better quality of life.

### 5.2. Scope of the work

The future scope of automatic early stress and non-stress detection analysis using supervised learning with Bayes' theorem is vast and promising. Here are some potential areas of development:

**Integration with wearable technology:** The integration of stress detection algorithms with wearable technology such as smartwatches and fitness trackers can provide continuous monitoring of stress levels in real time.

**Personalization of interventions:** With the help of machine learning algorithms, personalized interventions can be developed to manage stress levels more effectively. These interventions can be tailored based on the individual's unique stress response patterns.

**Collaboration with mental health professionals:** Automatic early stress and non-stress detection analysis can be used to complement the work of mental health professionals by providing an objective assessment of stress levels.

**Extension to other mental health conditions:** The technology can be extended to detect nervousness and unhappiness, allowing for earlier interventions and better outcomes.

**Integration with other data sources:** Integration with other data sources such as social media activity and electronic health records can provide a more comprehensive understanding of an individual's stress levels and overall mental health.

In future work, we are planning to propose a Stress Detection Framework with Data pre-processing. In data pre-processing, the noisy and incomplete data will be removed. Overall, the future scope of automatic early stress and non-stress detection analysis is promising, with the potential to improve mental health

outcomes for individuals and society as a whole. A plan to detect stress from multilingual stress words, apart from English. Subsequently, plan to enhance SDF for other languages based on various features like location-based, cultures, different people, and their nature of use.

## Author contributions

Conceptualization, MT and MK; methodology, MT; software, MT; validation, MT, MK and MM; formal analysis, MT; investigation, MT; resources, MT; data curation, MT; writing—original draft preparation, MT; writing—review and editing, MT; visualization, MT; supervision, MK; project administration, MT; funding acquisition, MK. All authors have read and agreed to the published version of the manuscript.

## Conflict of interest

The authors declare no conflict of interest.

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