Handwriting-Based Emotion Recognition Using GNN

by

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Declaration

It is hereby declared that

1. The thesis report submitted is our own original work while completing degree at BRAC University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Approval

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Abstract

Emotion detection is essential to know human behavior, but handwriting,a quite unique personal form of expression, remains underexplored in this context. This paper introduces a singular approach using Graph Neural Networks (GNNs) to locate feelings like depression, anxiety, and stress from handwriting. Utilizing the EMOTHAW dataset, we focus on dynamic capabilities such as ‘Azimuth‘, ‘Altitude‘, and ‘Pressure‘, which display significant versions and offer higher insights as compared to the historically used stroke range. After preprocessing the data, this was formatted in such a way that could be used for the model and turned into a version that was implemented to seize complex spatial and temporal relationships in handwriting patterns. The proposed method demonstrates the capability of handwriting as a sturdy modality for emotion detection and gives valuable insights into emotion-centered projects.

Keywords: EMOTHAW; Machine Learning; Emotion; Handwriting Analysis; GNN

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

EMOTHAW Emotion Recognition from Handwriting and draWing

GNN Graph Neural Networks

Chapter 1

Introduction

Emotion detection has been one of the major keys toward the understanding of human behavior and has gained sufficient attention through several modalities such as facial expressions, speech, and text analysis.[7] Of all these, handwriting is a unique and personal expression that reflects individual characteristics and emotions. In fact, a simple pen-and-paper test is able to disclose cognitive impairments in writing, especially in neurodegenerative diseases like Parkinson's and Alzheimer's, which affect attributes related to legibility, jaggedness, and persistence of letters. However, there has been relatively minimal research on handwriting as a method of emotion recognition.[7]

Determination of negative emotions early is crucial since negative emotions like depression, anxiety, and stress play a great role in determining general health. Depression, a complex mood disorder, is characterized by behavior disinterest and sad feeling, which can lead to impairments in social, occupational, and cognitive settings. Anxiety, on the other hand, is an aversive emotional state that might affect cognitive effectiveness. It is defined as the negative experience of emotion associated with predictable biochemical, physiological, and behavioral changes. Both the everyday challenges and major traumatic events cause stress. Since these emotions are the natural responses to the changes in life, persistent endurance can result in serious mental health disorders.

This paper proposes an approach for sentiment recognition using handwriting analysis using Graph Neural Network (GNN). By exploiting the structure of handwriting samples, GNN can effectively capture the relationships and patterns associated with emotional states in handwriting. The proposed method uses the EMOTHAW dataset of handwriting feature samples rated with corresponding emotions based on the DASS 42 questionnaire, a reliable psychometric instrument

Various signature features such as shock dynamics, spatial patterns, and graph attributes are extracted from the collected samples. The GNN model is trained on these features for sensitivity classification, and handles the multidimensional handwriting data well. Through optimization techniques, including regularization and cross-validation, the model aims to achieve high accuracy in sentiment prediction

Experimental effects exhibit the effectiveness of the proposed GNN-primarily based approach in appropriately detecting emotions from handwriting. The comparative analysis with present emotion detection techniques highlights the benefits and precise insights presented by analyzing handwriting as a modality. This method indicates promising capacity for real-world programs, such as psychology research, customized remarks systems, and emotion-conscious consumer interfaces. Overall, this have a look at affords a compelling case for handwriting as a precious modality for understanding and detecting human emotions, paving the manner for further studies that combines more than one modalities for a comprehensive emotion detection machine.

1.1 Problem Statement

Emotion detection from handwriting has won interest as a potential method for assessing psychological states. Previous research have explored diverse features extracted from handwriting, inclusive of stroke dynamics, stress, and spatial styles, to expand predictive fashions for classifying feelings. However, a vital obstacle arises from relying closely on certain features, including stroke variety, as signs of emotional states.

In the referenced study[7], the authors applied stroke variety as a number one feature for emotion detection. Stroke number is defined as the whole matter of wonderful strokes made in every handwritten sample. While stroke number might also offer a few insights into the fluidity and complexity of handwriting, it's been discovered that this metric may be relatively variable throughout individuals, frequently main to similar stroke counts among specific customers no matter their emotional states. Such similarities may be attributed to the fact that stroke variety isn't always inherently connected to emotional expression however rather reflects individual handwriting habits that won't trade notably across various emotional contexts.

From this number We can see how calculating the number of strokes from the feature 'pen status' gives almost the same information. In this analysis, the author found that some files produced almost identical data in the stroke count. From this observation, The number of strokes may not be the ideal parameter for detecting emotions.

When the authors from different researches compared stroke rates across multiple controls, they found that stroke rates were more consistent, providing a more realistic stroke number as a reliable standard attenuating this emotion recognition This finding suggests that using tumor number as an independent variable fails to capture subtle emotional encoding in gestures. Consequently, it is clear that the shock level does not adequately represent the emotional state, resulting in possible misclassification of patterns of emotion recognition.

This raises an important issue in handwriting-based emotion detection that relying on simple or superficial features can lead to inefficient and inaccurate emotion assessments and is therefore important early if more complex materials and techniques are required that can better capture the complexity of handwriting and its relationship to emotion states that there is a need.

Since stroke counts might not provide a reliable correlation amongst capabilities and can bring about overlapping information from time to time, the author of this paper took a distinctive method. First, they analyzed the connection between features with the use of a correlation matrix for every users. By analyzing correlation matrices generated from statistics through special customers, it turned into found that most matrices indicate a fine correlation among the capabilities—azimuth, altitude, and pressure. One such correlation matrix is shown right here as an example.

Considering all the correlation matrices created from the participants' data, It is clear that the data from the features i.e.- pressure, azimuth, will show positive correlation in most cases.

Before moving to different data frames The author must assess the reliability of the features. To determine whether it is worth analyzing or not. It turns out that highlighted information behaves differently in tasks compared to writing tasks. If shown visually through a graph Pressure data from drawing works well. But in the case of writing tasks it provides more consistent results for different users. Compared to the versatility of azimuth and elevation angles These characteristics still vary for all types of task. It provides valuable insights into exploring different methods.
In this context, features such as azimuth and elevation have been shown to have considerable variability across perceptual states. Azimuth which measures the horizontal angle of writing, the height of the vertical pen position during writing provides valuable insight into handwriting dynamics Unlike stroke numbers these features are highly sensitive to change occurring in emotional expression, and revealing nuances in how emotion influences handwriting behavior.

This study proposes a graph neural network (GNN) approach to explore the complex relationships and structures of signatures to address the limitations of dependence on stroke rates. This study attempts to demonstrate the potential of GNNs in capturing deep sensory information in gestures, thereby contributing to more accurate and meaningful sensory recognition systems.

1.2 Research Objective

The main objective of this study is to develop a robust and accurate emotion recognition model using handwriting analysis, using the Graph Neural Network (GNN) approach. This study aims to overcome the limitations of existing methods that rely on factors such as stroke number, which have been shown to be invariant enough to distinguish between different sensory states Our method seeks to more subtle handwriting features including azimuth and elevation will be combined.

Correlation matrix analysis of the dataset revealed negative correlations between several key factors, indicating that simple linear fits may not adequately capture complex dependencies and patterns in the data This finding emphasizes importance emphasizing the need for sophisticated modeling technique such as GNN.

[2] Furthermore, this research comes from the perspective of investigating the capabilities of GNNs in understanding and modeling complex handwriting data structures By using GNNs, we are not aiming for accurate emotion recognition aim not only to improve but also to contribute to the development of handwriting-based research through robust and comprehensive modeling. This approach seeks to establish a new standard for identifying emotion from handwriting, and to provide a deeper understanding of how emotional states manifest in written texts.

Chapter 2

Related Work

2.1 Findings on Emotion Recognition

[6]Handwriting analysis seeks to understand the way in which a person's handwriting tends to be related to his or her personality, considered as "brain writing" because it represents cognitive processes. Similar to fingerprints, no two individuals share the same handwriting, and this unique characteristic of the individual offers much insight into their emotions. The conventional approach to handwriting recognition depends upon professional personnel analyzing the samples by hand for extracting the personality traits, which is usually tiresome and cumbersome. This following research proposes a computer-based system that utilizes the machine learning algorithm known as K-Nearest Neighbors to predict personality traits based on handwriting samples. Their approach, in the modern context where several techniques are being taken into consideration for personality analysis like facial expressions, voice, and graphology, is based on multi-feature analysis, ranging from letter size and word spacing to slant, pen pressure, and baseline orientation. In integrating these features, we hope to arrive at more efficient and more accurate personality predictions using graphology.

[7]This work examined the relationship between emotional states and handwriting patterns by processing the data from 129 users performing seven different tasks of feature engineering, correlation analysis, and reducing dimensionality by LDA and PCA. Further, the Random Forest model was applied for the prediction of emotional states based on extracted handwriting features and showed promising accuracy in classification. The findings bring into focus that the handwriting data may represent a practical method of emotion detection and therefore provide an initial point for further work in this area.

Recently, more and more research efforts have been targeted at emotional aspects in interactions, in particular those touching on therapeutic relationships.[1] This case study explores the aspect of emotions in the interactions between PTs and their patients within psychiatric settings using a qualitative cross-case analysis in line with Shephard et al. (Citation). The eleven participants in this study were experts regarding interactions with patients, and all identified the role of emotions in making for effective therapist-patient relationships. Results underlined the importance of PTs recognizing and expressing their emotions, identification of patients' emotions, and emotional expression assistance to patients. Emerging themes included: emotions as a foundation for communication, balancing a PT's own emotions against the patient's; motivational aspects of emotions in treatment; body language; and the facilitation of emotional awareness in patients. The results of this study are discussed in the light of prior theories on the role of emotions within therapeutic relationships.

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[6]In the article, In order to recognize multimodal emotions during human-robot interaction (HRI), this paper introduces a Kernel Canonical Correlation Analysis (KCCA) approach based on K-means clustering. The method combines multimodal data taken from voice and facial expressions, increasing heterogeneity between various modalities and raising identification rates. In order to choose features and reduce dimensionality, K-means clustering is used. The suggested method surpasses those that do not use K-means clustering, as shown by experiments on the SAVEE and eNTERFACE'05 datasets, which achieved a recognition rate of 87.20 percent, beating the other methods by 1.23 percent. This method illustrates the possibility of multimodal fusion in emotion recognition, which is pertinent to the discussion of multimodal analysis in the evaluation of Parkinson's disease.

2.2 Works on Handwriting Analysis

[4] The study investigates the use of handwriting analysis and physiological signs in the early identification of Parkinson's disease (PD). The research makes use of a variety of classifiers and ensemble techniques with a subset of the PaHaW dataset that include early to mild PD cases. Important results and limitations include: The accuracy and sensitivity of the Random Forest classifier are both 73.38 percent and 62.07 percent, respectively. The most effective outcomes are highlighted as task-specific accuracy is displayed. The combination of the three tasks with the greatest performance results in accuracy of 74.76 percent and sensitivity of 68.97 percent. This Study's proposed technique is unclear, which is a negative. These findings imply the possibility of using handwriting dynamics for an early PD diagnosis. De-

spite this hope, the methodology of the study may use some better articulation. For improved clinical assessment and illness management, this strategy shows promise.

This study [8] aimed to develop, through graph analysis and with the support of handwriting signals, machine learning models for the screening and telematic monitoring of a progressive neurodegenerative disorder: Parkinson's disease. The disease presents both motor and non-motor symptoms, one characteristic of the disease being that those symptoms deteriorate with time. Common motor symptoms include bradykinesia, tremors, muscle rigidity, and balance problems that result in dysgraphia, such as the reduction in size of handwriting termed as "micrography". Handwriting pattern analysis may allow earlier diagnosis and monitoring of disease progression. Data were acquired from 16 Parkinson's patients and 42 healthy controls by means of a protocol consisting of drawing and writing tasks performed remotely by participants using a graphic tablet with pen position, inclination, and pressure recording. The research work focused on the extraction of relevant features, the selection of such features by statistical methods, and developed models with accuracy rates higher than 90 percent, hence proving promising compared to the existing literature. It also updated, for a study, a mobile application to both iOS and Android versions which can collect handwriting data along with voice in real time for storage and remote monitoring.

The goal of this [8] study is to create machine learning models for graph and handwriting signals to screen for and monitor Parkinson's disease. Parkinson's disease is a neurodegenerative condition marked by progressive motor and non-motor symptoms. Bradykinesia, tremor, muscle rigidity, balance problems, and postural instability are examples of motor symptoms. Dysgraphia, which can also impact handwriting, might result in "micrography." Using a graphic tablet with real-time data gathering, data from 16 parkinsonian and 42 healthy patients were remotely gathered. distinct machine learning models were created by extracting distinct properties. These models demonstrated high accuracy values that exceeded 90 percent, sometimes beating previous research. The study also provided updates to an iOS and Android application that allowed for the real-time gathering and storing of audio and graphic signals. It is noteworthy that the study discovered that some tasks, like Sentence 1, demonstrated the best performance, probably as a result of the informational contribution of letters occupying both high and low regions of reference values. These results are in line with the overarching objective of improving patient care and management and helping to develop useful tools for early Parkinson's disease diagnosis and monitoring. Although the study's main focus is handwriting analysis for Parkinson's disease, it also provides insightful information about potential multimodal methods and diagnostic equipment for neurodegenerative diseases, which is tangentially related to the subject of the current paper.

Chapter 3

Data Analysis

3.1 Proposed Methodology

To make the data consistent and accurate before training the model,the data needs to be preprocessed.

Data Cleaning: Preprocessing steps include cleaning the data, which involves separating the handwriting features initially located in one column as strings, separated by space into different columns for each feature. That would make such data manipulations a bit easier to do. Inconsistent or missing values were then detected, such as undefined 'Pen status' or incorrect 'Timestamp' entries. Minor gaps were filled through interpolation and records containing large quantities of missing data likely to impact the analysis were removed.

Normalization: To ensure that all the features contribute equally to the analysis, normalization was applied to features like 'x-position', 'y-position', 'Pressure', and 'Timestamp'. It would minimize biases that could emanate from the use of different measurement scales.

Feature Extraction: Additional features, such as in-air duration and on-paper stroke duration, were derived from the 'Timestamp' and 'Pen status' values. These features will be of great importance in reflecting nuances in the handwriting patterns that may indicate emotions through hesitations or changes in stroke dynamics.

Data Labeling: Prior assessment and self-reporting were used for labeling each segment of the dataset with emotional states such as 'depression', 'anxiety', and 'stress'. These labeled datasets allow for supervised training for emotion classification.

Data Augmentation: Since diversity is very important in a dataset, a few data augmentation techniques were performed to help make the model more robust. Rotation and scaling are among the augmentation techniques applied on handwriting trajectories, which in turn simulate variations in input data, ensuring that the model generalizes well over a wide range of handwriting patterns.

Preprocessed and labeled segments of data will then act as input for different phases in model development.

3.1.1 Data Preprocessing

The first dataset was space-seperated, meaning that all features were contained in a single column. In the first step, this column is divided into several meaningful characters such as ‘x-position‘, ‘y-position‘, ‘Timestamp‘, ‘Pen position‘, ‘ Azimuth‘, ‘Height‘, and ‘Pressure‘

The data was separated into categories, followed by further data cleansing to ensure that the data was accurate and usable for use, and to address any missing or inconsistent values.

Two features such as ‘Azimuth‘ and ‘Altitude found‘ to be important, due to their ability to show variability with different sensory states, as opposed to simpler items such as the number of strokes, which showed less variation among them use the contrast

3.1.2 Data Handling

Cleaning and Structuring: The first row of the data (likely metadata) was removed to isolate useful numerical values.Columns were renamed to more descriptive names such as:‘x-position‘, ‘y-position‘ (spatial coordinates), ‘Timestamp‘ (time-related data),‘Pen status‘, ‘Azimuth‘, ‘Altitude‘, and ‘Pressure‘ (handwriting features).
Handling Missing Values: Data types for relevant columns were converted to numeric using ‘pd.to numeric‘, with errors replaced by ‘NaN‘.Missing values were filled with zeroes, ensuring consistency.

3.1.3 Feature Engineering

Graph Construction

‘x-position‘ and ‘y-position‘ were combined into a matrix for spatial proximity calculations.Euclidean distances between all data points were computed using ‘distance matrix’.An adjacency matrix was generated by applying a distance threshold to determine node connectivity.

Temporal Proximity

A separate matrix for time differences (‘Timestamp‘) was computed to assess temporal adjacency.Combined spatial and temporal adjacency matrices were created using logical operations.

Pressure Weights

A pressure-based adjacency weight matrix was computed by transforming pressure differences into exponential weights.

Adjacency Matrix Normalization

The adjacency matrix was normalized to prepare it for input into Graph Neural Networks (GCN), ensuring numerical stability.

Labeling

Additional columns were added to label the data with emotional states, such as 'Depression', 'Anxiety', and 'Stress', using predefined values.

Outcome

The processed data included the normalized adjacency matrix and feature-rich data for use in building a GNN model.

3.2 Building GNN Model

Graph Creation:
Converted handwriting data into a graph structure, each time the stamped point of the handwriting trace was used as a node, and the temporal relationship between the points was used to form the graph anoano -Edges were determined based on the chronology of the data, and each row was connected to its next row, thereby creating a graph representing the manuscript process.

Node attributes:
Each node in the graph was enforced with attributes such as 'x-position', 'y-position', 'Azimuth', 'Altitude', and 'Pressure'. This strategy enabled the GNN model to take advantage of both spatial and temporal information in the handwriting data.

Model Design:
The GNN model is constructed using a series of Graph Convolutional Network (GCN) layers. These layers enable the model to collect information from neighboring nodes, capturing the local and global structure of the graph. - The model consisted of two GCN convolutional layers, where the first layer mapped the input features into high-dimensional space to identify complex relationships, and the second layer refined these representations for simplicity to be evenly distributed - Added Dropout layers to prevent overfitting and to ensure generalizability of the model.
Training and Adjustment: - The model was trained with the elements of the selected nodes, where each node represents a part of the signature trace. The goal of the training was to classify these facets based on emotional states (e.g., depression, anxiety, and stress) derived from the DASS scores in the data set - Loss functions such as cross-entropy loss were used in training, while optimization techniques such as ADAM-optimizer were used to adjust model parameters for better performance - Added regularization techniques such as dropout and L2 regularization to prevent overfitting, and performed cross-validation to ensure that the model generalizes well to unseen data.

3.3 EMOTHAW Database

The referenced article [5] highlights the significance of early emotional state recognition and its implications in healthcare. Leveraging well-established tests from the literature, the study focuses on anxiety, stress, and depression as key emotional states. The DASS Scale (Depression-Anxiety-Stress Scale) offers a reliable questionnaire to correlate with handwriting tasks. The authors have created a database, called EMOTHAW (EMOTion recognition from HAndWriting and drAWing), using seven tasks of handwriting that were developed from cognitive and psychological assessments to diagnose the state of mind, cognitive skills, and even brain damage: CDT (Clock Drawing Test), MMSE (Mini-Mental State Examination), and HTP (House-Tree-Person Test). In addition, two tasks of writing have been conducted to study the influence of different tasks for emotion recognition.
This binary classification has completely removed the severity levels of the disorders, as each subject is classified either depressed or not, anxious or not, and stressed or not. Therefore, the resulting dataset features a binary-label output. Table 2 from [5] summarizes the threshold for "Normal" and "Above Normal" ranges in the DASS score scale. The dataset consists of seven tasks performed by 129 participants. The data files in the EMOTHAW dataset are divided into two main folders named Collection 1 and Collection 2. In Collection 1, data from 45 users are available; Collection 2 contains data from 84 users. In each of the user folders, a session folder is available that contains seven files corresponding to each of the following activities[3]:

1. Drawing a two-pentagon image
2. Drawing a house image
3. Writing, in block letters, four Italian words (BIODEGRADABILE, FLIPSTRIM, SMINUZZAVANO, CHIUNQUE)
4. Drawing loops with the left hand
5. Drawing loops with the right hand
6. Carrying out a clock drawing test
7. Copying in cursive a phonetically complete Italian sentence (I pazzi chiedono fiori viola, acqua da bere, tempo per sognare, that is to say, "Crazy people are seeking purple flowers, drinking water, and dreaming time").

Each file contains data with seven columns for the following features, respectively[3]:

1. X-axis position
2. Y-axis position
3. Timestamp
4. Pen status: up = 0, down = 1
5. Azimuth angle of pen with respect to the tablet
6. Altitude angle of pen with respect to the tablet
7. Pen pressure

3.4 DASS Scale

The Depression Anxiety and Stress Scale (DASS) was first proposed with its Italian version, I-DASS-42, comprising 42 items, and has been validated by Severino. It covers an emotional range of scores assessing whether the subject is under depression, anxiety, and or stress as outlined in the Table 1 from [5]. Utilizing DASS, scientists were able to establish tasks-emotion relationship by sorting for each subject's score under a group of levels.

Since the database only consisted of 129 subjects, the classification in Table 1 from [5] resulted in a considerable amount of outliers for most of the labels. Therefore, the scores were further binarized based on a simple threshold: Depressed: Scores for depression-related questions greater than 9 Anxiety: Scores for anxiety-related questions greater than 7 Stressed: Scores for stress-related questions greater than 14

Italian versions of the Depression Anxiety Stress Scales-I-DASS-42-measured the emotional states of the participants. Henry and Crawford originally constructed the validity of the DASS-42 for its English version in 2003. The DASS score file includes a calculated score for each of the subjects, amounting to 129 in total.

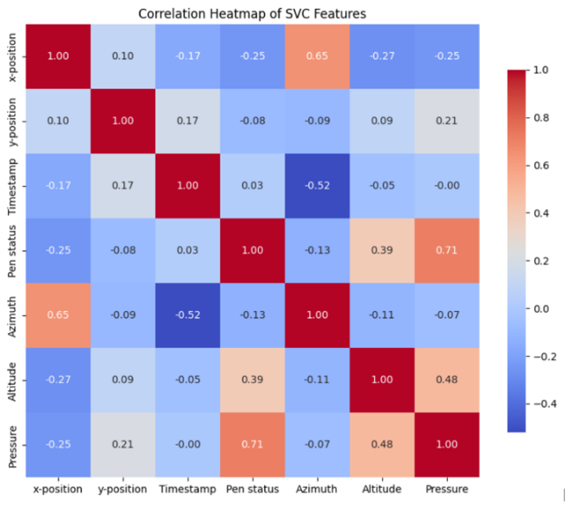

Figure 3.1: Correlation Matrix

Additionally, the correlation analysis performed at the dataset highlighted negative relationships amongst various features, further helping the choice of a GNN-based totally approach. This feature allowed the GNN to efficiently version the elaborate dependencies and interactions within the dataset, shooting the subtle versions in handwriting which are indicative of various emotional states. The model's stability and ability to generalize throughout one-of-a-kind handwriting samples underscore its capability suitability for actual-global packages in emotion detection. The consequences emphasize that leveraging GNNs for this venture is a promising path, supplying more advantageous insights into the connections between handwriting dynamics and emotional states.

Chapter 4

Result Analysis

The proposed GNN approach was initiated with a graph attention mechanism to understand the contribution of each feature as nodes, thus it was trained with the EMOTHAW dataset. Throughout the training, the GNN effectively modeled the spatial and temporal connections in handwriting samples containing files using graph structures. The adjacency matrix allowed the GNN integrate data from neighbouring nodes, capturing handwriting features between strokes which gives results to understand the possibility of any discrepancy could occur if we consider stroke as the parameter for the research. In this training process, the loss function reduction played the keyrole to understand the efficiency of the GNN. This approach can be evidenced the steep reduction in loss as the variety of epochs elevated, indicates the underlying ability of the data

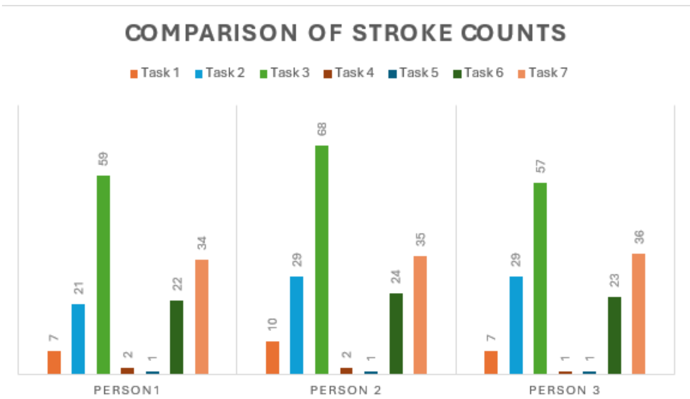

Figure 4.1: Comparison of stroke counts

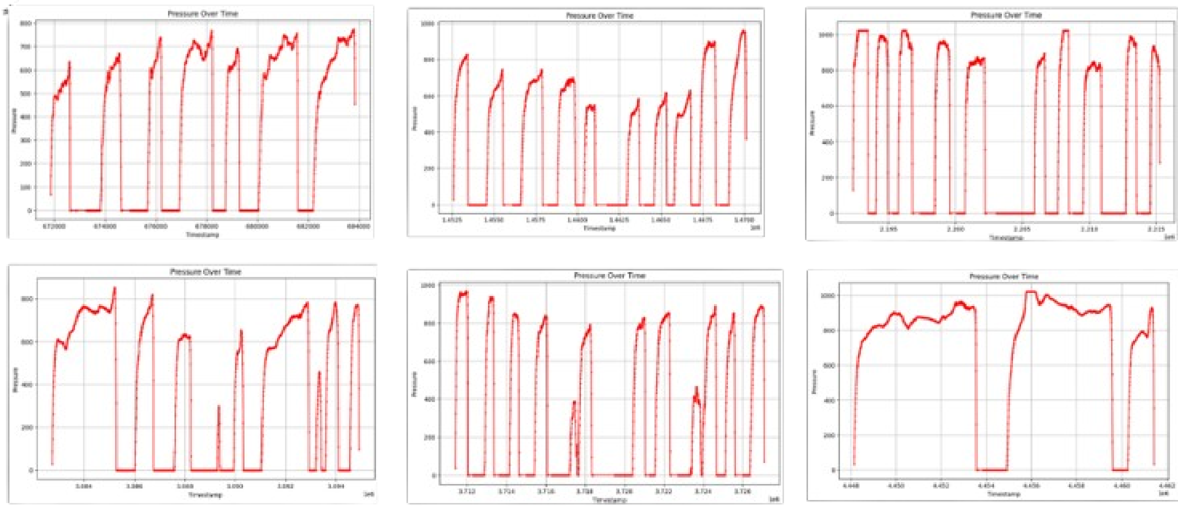

Figure 4.2: Comparison of pressure of drawing task

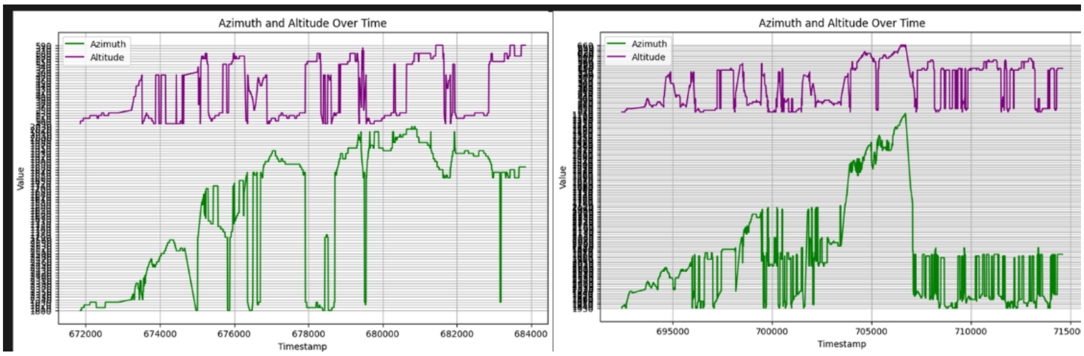

Figure 4.3: Comparison of azimuth and altitude of drawing task

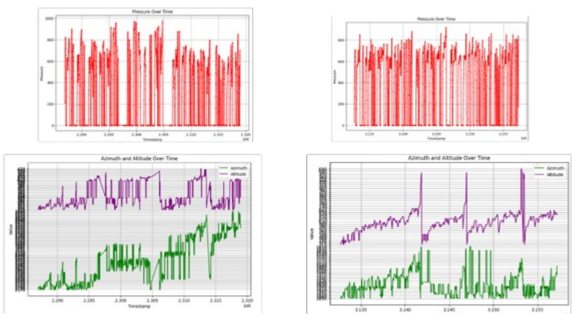

Figure 4.4: Performance for writing task

4.1 Outcome From Model

The training process of the GCN model, as shown by the epoch vs. loss graph and detailed loss values, is steadily converging to the best performance. The training loss starts high at the beginning, which reflects the raw state of the model before learning the patterns from the data. However, during training, the loss decreases drastically, at least for the first 20 epochs, which shows that the model is learning well and optimizing its parameters toward the best fit. Beyond 30 epochs, the loss stabilizes at much lower values, showcasing the model's convergence and reduced error rates. This consistent decline in loss is indicative of the generalization capability of the GCN model in learning from the dataset and thus is capable of accurate emotion detection based on the features of the task.

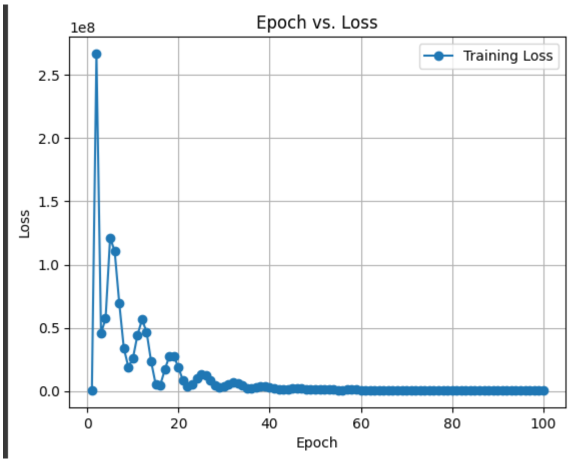

Figure 4.5: Epoch and Loss Graph

The author found that mere stroke count might introduce discrepancies in the handwriting analysis; hence, the author chose to go for other parameters that would present a wider perspective and, in fact, more minute details about the features of handwriting. This will make the analysis not only more reliable but also more insightful, since different angles and perceptions of the data are captured.

4.2 Thoughts

This section assesses the performance of the GNN model developed for emotion detection from handwriting. The main goal of this model is to classify the emotional states, such as anxiety, depression, and stress, by taking advantage of the spatial and temporal features of handwriting data from the EMOTHAW dataset.
It has targeted analyzing graph-based trajectories of handwriting data with a much higher degree of precision of detecting emotional states. Since it uses GNN, capturing spatial relations of these features such as pressure, pen tilt, and even time-series data becomes more easy than in any other ML methods.

Chapter 5

Conclusion

This paper presents an approach for sentiment detection using gesture analysis using a graph neural network (GNN) model. The research explores the potential of handwriting as a means of identifying emotional states such as depression, anxiety and stress. While previous methods rely on simple metrics such as stroke number, which cannot capture large variations among users, our approach focused on more dynamic features such as 'Azimuth ' and 'Altitude' on, as well as other spatio-temporal aspects of the handwriting Allowed me to model and capture subtle handwriting changes indicative of emotional states.

The results show that the GNN model effectively utilizes the fine-grained handwriting information to generate accurate predictions of emotional states. The use of GNNs benefits from capturing complex spatial and temporal patterns of handwriting, providing deeper insights into how emotions are expressed in handwriting Correlation analysis prior to model training revealed negative correlations between certain elements, and also highlighted the importance of models that can handle nonlinear interactions such as GNNs.

Compared to traditional machine learning models, GNN not only improved prediction accuracy but also provided a more nuanced understanding of data using graph-based methods Model performance on the EMOTHAW dataset shows that handwriting can has been an effective way of detecting emotions.

This study opens the door for further investigation of graph-based models for human activity analysis, and highlights the potential for combining multiple approaches to develop more robust emotion recognition systems.

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