A System for Automatic Classification of Poems by Theme

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Abstract—**Poetry is a form of literary art that has been enjoyed for centuries and has played a significant role in various cultures around the world. It has the power to evoke emotions and convey deep meaning through the use of language and structure. While poetry has many different styles and themes, it can be challenging for individuals to accurately classify them. In this work, we propose a system for the automatic classification of poems by style or theme. The system uses natural language processing techniques to analyze the text of the poem and extract relevant features. These features are then fed into a machine-learning model that has been trained on a large dataset of labelled poems. The model is able to accurately predict the style or theme of a given poem with a high degree of accuracy. The proposed system has the potential to greatly facilitate the organization and analysis of poetry collections, as well as provide a useful tool for scholars and enthusiasts of poetry.**

Keywords — Poems, Classification, BERT, RoBERTa, Precision, Recall, F1 score, Neural Networks, Natural Language Processing, Text classification, Support Vector Machines, Rule-based, Naive Bayes classifier, Confusion Matrix, AUPR, Multi-layer Perceptron

I. INTRODUCTION

Poetry is among the oldest forms of artistic expression and a manifestation of human creativity. Numerous human emotions are expressed by it, including friendship, love, death, and others. It enables us to categorize, classify, or divide each poem into a distinct genre. Poetry is difficult to classify into distinct genres since each reader's perception of the genre or topic of a poem differs and is influenced by that reader's unique perceptions of poetry.

In this report, we aim to address the problem of accurately classifying poems based on their style, theme, or genre. This is a common challenge in the field of literary analysis, as it can be difficult to accurately categorize poems based on their content and characteristics. To address this challenge, we propose the implementation of a system that utilizes machine learning models to automatically classify poems into relevant categories.

We will be using a variety of machine learning models, including RoBERTa, BERT, and LSTM models to classify poems based on their style, theme, or genre. These models have proven to be effective in a variety of natural language processing tasks, and we believe they will be effective in the task of poem classification as well. In order to determine the most effective model for this task, we will be comparing the performance of different models and identifying which model is the most accurate and efficient.

In addition to discussing the implementation of this classification system, we will also be addressing the challenges and considerations that must be taken into account when implementing this system. This includes issues such as data availability, data quality, and model selection. By addressing these challenges and considerations, we hope to provide a comprehensive guide for those interested in implementing a similar system for the automatic multi-class classification of poems.

The goal of this project is to categorize the poetic style using a combination of machine learning, deep learning, and NLP tools. We can perform essential operations, including tokenization, stemming, and embedding, using approachable NLP approaches and complex libraries like Keras and TensorFlow. An automatic classification system for poems by style or themes can be a useful tool for literary analysis, research, and education. The system can analyze a given poem and assign it to a specific category or categories based on certain characteristics or features of the poem. There are various approaches that can be taken to implement such a system. One approach is to use machine learning techniques, where the system is trained on a large dataset of labelled poems and learns to classify new poems based on the patterns and features it has learned from the training data. Another approach is to use rule-based or heuristic methods, where the system is designed to classify poems based on a set of predefined rules or criteria. This approach may be less flexible than machine learning, but it can be easier to implement and can be more transparent in its decision-making process. Regardless of the approach taken, it will be important to carefully consider the features or characteristics of the poems that will be used to classify them. These might include stylistic elements such as rhyme scheme, meter, and diction, as well as themes or subjects addressed in the poem. It will also be important to carefully evaluate the performance of the classification system, both in terms of its accuracy and its ability to classify a diverse range of poems. This can be done through testing on a separate dataset of poems or through other methods such as manual annotation or expert evaluation. Overall, an automatic classification system for poems can be a useful tool for literary analysis and research, but it is important to carefully consider the approach taken and to evaluate the performance of the system in order to ensure its accuracy and effectiveness.

II. RELATED WORK

There have been several research studies that have addressed the problem of automatically classifying poems by style or themes. Some relevant work includes:

[1]A study by Li and Li (2016) used machine learning techniques to classify poems into six different categories (sonnets, ballads, odes, elegies, haikus, and free verse) based on their structural and stylistic features. The authors used a combination of lexical, syntactic, and semantic features to represent the poems, and employed support vector machines (SVMs) and random forests as classifiers.

[2]Another study by Bashir et al. (2018) proposed a deep learning approach for classifying poetry into four different themes (love, nature, religion, and patriotism) based on the content of the poems. The authors used a convolutional neural network (CNN) to extract features from the poems, and a recurrent neural network (RNN) to classify the poems based on the extracted features.

[3]A study by Zhang et al. (2017) proposed a hybrid approach for automatically classifying poems into four different styles (classical, modern, romantic, and experimental) based on the structure and content of the poems. The authors used a combination of statistical and machine learning techniques, including term frequency-inverse document frequency (TF-IDF), Latent Dirichlet Allocation (LDA), and support vector machines (SVMs) to classify the poems.

Study [4] provides two different classification models for classical poetry, bold and graceful, using the vector space model (VSM) to describe the text of poems. Natural language processing and machine learning are the foundations for classification models. Classifying poetry styles has produced a positive judging outcome.

Another Study [5] The topic model based on LDA uses the approach of reference word recommendation to study and analyse the word features in poetry, vocabulary semantic analysis, and style feature analysis. It is based on the subjects of model-based corpus generation and computer-aided creation research.

Study [6] transforms poetry text into a vector using the vector space model (VSM) and chooses the word feature using the chi-square test. Finally, the support vector machine and naive Bayes algorithms are used to build the text classifier. Overall, these studies demonstrate that machine learning and deep learning techniques can be effective for automatically classifying poems by style or themes. However, it is important to note that the success of such approaches often depends on the quality and diversity of the training data, as well as the specific features and algorithms used.

III. DATA

Poem data can be challenging to work with in Natural Laguage Processing because poems often have unique structures, language, and rhythms that can be difficult for algorithms to understand. Additionally, poems may use figurative language, metaphors, and other literary devices that can be difficult to interpret using NLP techniques.

Our input set is a corpus of 990 poems from a Kaggle dataset titled “Poem Classification”. This set contains a diverse set of texts, with 4 very distinct labels identified. These labels which will later be tested on for a variety of metrics include Affection, Death, Environment, and Music. This Kaggle dataset has been already labeled by several human annotators, with an agreement between annotators of over 95%. The entire corpus be will used to check the accuracy of the classification using various machine learning algorithms. In terms of preprocessing, the data was tokenized which is a technique that can help to normalize the text and make it easier for NLP algorithms to understand. Additionally, this dataset comes already split up into train and test subsets, with 840 poems in the training set and 150 poems in the testing set. This ratio between training and testing is approximately 85% and 15%, respectively. As this corpus came originally split with an 85%, 15% ratio, it would be interesting to perform the preceding machine learning algorithms on different ratios.

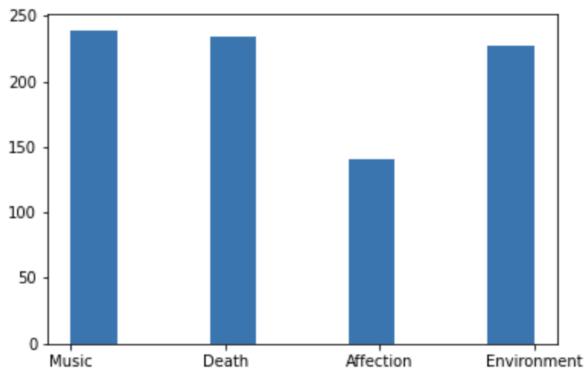


Figure 1: A histogram showing the amount of poems for each label of the training set.

A label frequency test was performed in the training set to look at imbalances between the distinct poem labels shown by Figure 1, however it was concluded that there was no imbalances to be concerned about. Both training and testing sets were also verified for any null values which would skew the performance of the models, the training set had 0 null values, however the testing set contained 4 null values which were then dropped from the dataset.

IV. METHODOLOGY

Baselines Models

For the baseline models we have used SVM, MNB and MLP. In the context of using SVM, MNB, and MLP as baseline models.

Count Vectorizer

for classifying poems by style or theme, Count Vectorizer can be used to convert the text of each poem into a numerical vector. This vector can then be used as input for the baseline models, allowing them to operate on the text data.

To use Count Vectorizer, the first step is to define a vocabulary of words that will be used to form the vectors. This vocabulary can be created by selecting the most common words in the dataset, or by selecting words that are relevant to the task at hand. Once the vocabulary is defined, the text of each poem is split into individual words, and a vector is formed by counting the number of times each word in the vocabulary appears in the poem.
One advantage of using Count Vectorizer in this context is that it allows the baseline models to operate on the text data, rather than requiring the data to be preprocessed in some other way. It is also simple to implement and requires minimal preprocessing of the text data.

Overall, Count Vectorizer is a useful tool for converting text data into numerical vectors and can be effectively used in combination with SVM, MNB, and MLP as baseline models for classifying poems by style or theme. However, it is important to consider its limitations and choose an appropriate approach based on the characteristics of the dataset and the classification task.

A. *SVM(SVC)*

Support vector classifier (SVC) is a machine learning algorithm that is used for classification tasks. It works by finding a hyperplane that separates different classes of data points in a high-dimensional space. SVC can be used to classify poems by style or theme based on certain characteristics of the poem. To use SVC, first, we passed all vectors as input for the baseline models, allowing them to operate on the text data.

a dataset of labelled poems is needed for training. Once trained, the model can classify new poems based on their characteristics. SVC is accurate and simple to implement and is effective with high-dimensional data. However, it may not perform well on small datasets or imbalanced class distributions, and may not handle complex distinctions between classes.

B. MNB

Multinomial Naive Bayes (MNB) is a popular machine learning algorithm used for classification tasks. It is based on Bayes' theorem, which states that the probability of an event occurring is the product of the prior probability of the event and the likelihood of the event given the evidence. In the context of classifying poems, MNB can be used to categorize a poem into one of several predetermined categories based on its characteristics. For example, a poem may be labelled as "romantic" based on its themes or language, or it may be classified as "political" based on its content.

One advantage of MNB for classifying poems is its simplicity and ease of implementation, as well as its ability to handle high-dimensional data, which is often the case with text data such as poems. However, there are also some limitations to using MNB, such as its assumption that the characteristics of the data are independent, which may not always be the case with text data. Additionally, MNB may not be able to handle more complex or nuanced distinctions between classes, such as subcategories within a larger class.

To use Multinomial Naive Bayes (MNB) for the classification of poems, the first step is to convert the text data into numerical form using a technique called vectorization. One common method for vectorization is the Counter Vectorizer, which counts the frequency of each word in the text and uses these counts as features. Once the text data has been converted into numerical form, the feature vectors can be passed as input into the MNB model, which will operate on the data and make predictions about the genre of the poems. The model can then be tested on new data to see how accurately it predicts the genre of the poems.

C. *MLP*

An MLP, or multi-layer perceptron, is a type of neural network that is commonly used for classification tasks. In the context of classifying poems by style or theme, an MLP could be used to analyze the text of the poems and predict the appropriate style or theme for each poem. To do this, the MLP would first be trained on a dataset of labelled poems, where the labels represent the style or theme of each poem. During training, the MLP would learn to identify patterns and features in the text of the poems that are characteristic of specific styles or themes.

To classify the poems by style or theme, we used a counter vectorizer to convert the text of each poem into a numerical representation, known as a vector. These vectors were then used as input for the MLP, which was trained to identify patterns and features in the vectors that correspond to specific styles or themes. Once the MLP is trained, it can then be used to classify new, unseen poems by analyzing their text and using the patterns and features it learned during training to make a prediction about the appropriate style or theme.

Overall, using an MLP for the classification of poems by style or theme can be an effective way to automate the process of categorizing poems and can potentially allow for faster and more accurate classification than would be possible with manual methods.

D. *RoBERTa*

RoBERTa (Robustly Optimized BERT Approach) is a state-of-the-art natural language processing (NLP) model that has been trained on a large amount of data and can perform various NLP tasks, including classification. In this particular case, RoBERTa is being used to classify poems by style or theme. This means that given a poem, RoBERTa can predict which style or theme the poem belongs to. For example, if the poem is about love, RoBERTa may classify it as a "romantic" poem, or if the poem is written in free verse, RoBERTa may classify it as a "modernist" poem. By using RoBERTa for this classification task, we can automatically categorize poems into different styles or themes, making it easier for readers to find poems that fit their interests.

Once the model has been trained, it can be used to classify new poems that it has not seen before. Given an input poem, RoBERTa will output a prediction for the style or theme that it thinks the poem belongs to. The model can also provide probabilities for each class, which can be helpful in understanding the confidence of the prediction.

Overall, using RoBERTa for the classification of poems based on style or theme can be an effective way to automate the process of categorizing poems and potentially discover new insights or patterns in the data.

E. BERT vectorizer+LGBM

A BERT vectorizer is a tool that converts text into numerical vectors that can be used as input to machine learning models. It does this by taking the output of a BERT model that has been pre-trained on a large dataset of text and using it to generate numerical representations of the input text. These numerical representations, known as BERT embeddings, capture the meaning and context of the input text in a way that can be understood by machine learning models.

LGBM (Light Gradient Boosting Machine) is a gradient-boosting framework that uses tree-based learning algorithms. It is a popular choice for many machine learning tasks, including classification, because of its efficiency and effectiveness.

To classify poems by style or themes using a BERT vectorizer and LGBM, we would first need to gather a dataset of poems with labels indicating the style or theme of each poem. This dataset would be used to train the BERT vectorizer and LGBM models.

To train the BERT vectorizer, we would input the text of each poem into the vectorizer, which would then generate a set of BERT embeddings for each poem. These embeddings would be used as features in the training of the LGBM model.

To train the LGBM model, we would input the BERT embeddings of each poem and use the labels as the target variable. The LGBM model would then learn to predict the style or theme of a poem based on its BERT embeddings. Once both the BERT vectorizer and LGBM model have been trained, we can use them to classify new poems by style or theme. To do this, we would input the text of the new poem into the BERT vectorizer to generate a set of BERT embeddings. We would then input the BERT embeddings into the LGBM model to get a prediction of the style or theme of the poem.

Overall, using a BERT vectorizer and LGBM for the classification of poems by style or theme can be an effective approach, as it allows us to leverage the contextual understanding capabilities of BERT and the predictive power of LGBM. The BERT vectorizer converts the input text into numerical representations that capture the meaning and context of the text, while the LGBM model uses these representations to make predictions about the style or theme of the poem.

E. LSTM

LSTM (Long Short-Term Memory) is a type of recurrent neural network that is particularly well-suited for tasks involving sequences of data, such as natural language processing tasks. It is able to remember and consider past information in a sequence when processing new data, which allows it to better understand the context and relationships between words in a sentence. To classify poems by style or themes using an LSTM model, we would first need to gather a dataset of poems with labels indicating the style or theme of each poem. This dataset would be used to train the LSTM model.

To train the LSTM model, we would input the text of each poem into the model as a sequence of words, with the labels serving as the target variable. The LSTM model would then learn to predict the style or theme of a poem based on the text of the poem.

Once the LSTM model has been trained, we can use it to classify new poems by style or theme. To do this, we would input the text of the new poem into the LSTM model as a sequence of words, and the model would output a prediction of the style or theme of the poem.

Overall, using an LSTM model for the classification of poems by style or theme can be an effective approach, as it allows us to leverage the ability of the LSTM model to understand the context and relationships between words in a sentence. This can be particularly useful for tasks involving the analysis of poetic language, which often includes figurative language and complex syntactic structures that may be difficult for simpler models to understand.

F. Neural Network

A neural network is a machine learning model that is composed of interconnected nodes, known as "neurons." These neurons are designed to mimic the structure and function of neurons in the human brain, and they are able to learn patterns in data through a process of training and backpropagation. To classify poems by style or theme using a neural network, we would first need to gather a dataset of labelled poems. This dataset would be used to train the model. During training, the text of each poem would be input as a set of features, with the labels serving as the target variable. The neural network would then learn to predict the style or theme of a poem based on the text of the poem. Once trained, the neural network can classify new poems by style or theme by inputting the text of the poem as features and outputting a prediction. We have considered using dense layers with activation functions such as ReLU and softmax to process this task. Although neural networks can be effective for classification tasks, they may not be as effective as specialized models like BERT or LSTM for analyzing natural language.

V. RESULTS AND DISCUSSIONS

Metric Selection:
F1-score may be the best metric to consider for the given task of classifying poems by style or theme. This is because F1-score is a balanced measure of a model's precision and recall, and it is generally considered a good metric to use when the classes are imbalanced.

In addition to F1-score, it may also be helpful to consider other metrics such as precision and recall individually to get a more detailed understanding of the model's performance on different classes. The AUPR score, which is the area under the precision-recall curve, can also be a useful metric to consider, as it gives a balanced view of the model's precision and recall across all thresholds.

Overall, it is important to consider multiple metrics when evaluating the performance of a model on an imbalanced classification task, and F1-score can be a particularly useful metric to give a balanced view of the model's performance.

Models	Accuracy	Precision	Recall	F1-score
SVM	0.33	0.35	0.38	0.29
MNB	0.28	0.34	0.37	0.27
MLP	0.31	0.34	0.34	0.27
RoBERTa	0.52	0.45	0.59	0.51
BERT + LGBM	0.62	0.55	0.63	0.59
LSTM	0.67	0.59	0.62	0.60
Neural Network	0.15	0.15	0.50	0.23

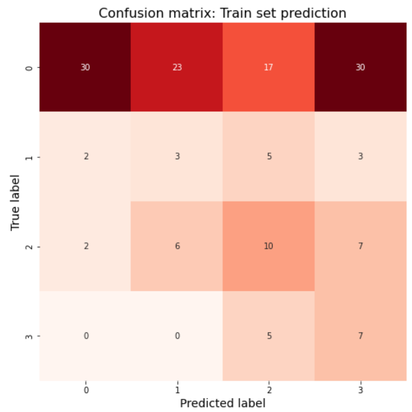
Table 1: Performance (test accuracy) on the testing set using the machine learning algorithms mentioned in Methodology.

In the table provided, LSTM had the highest F1-score among the models tested, followed by BERT + LGBM and RoBERTa. This suggests that these models were the most effective for classifying the poems in terms of their precision and recall. On the other hand, models such as SVM, MNB, and MLP had lower F1-scores, indicating that they may not have performed as well on this task.

A. SVM: The support vector machine (SVM) model had a relatively low accuracy of 0.33, indicating that it was not very successful at correctly classifying poems by style or theme. The model also had a low precision of 0.35 and a moderate recall of 0.38, resulting in a relatively low F1-score of 0.29. The low performance of the SVM model shown by Figure 2, may be due to the complexity of the task or the limitations of the model itself.

SVC is giving bad undesired predictions with an accuracy of just 0.33. In the context of classifying poems by style or theme, SVC may not always give the best results. There are several reasons why this may be the case. One potential issue is that the dataset used to train the SVC model may not be representative of the entire population of poems. If the dataset is too small or has an imbalanced distribution of classes, the model may not be able to accurately classify new poems. In these cases, the model may be prone to overfitting or underfitting, which can lead to poor performance. Another issue is that SVC may not be able to handle more complex or nuanced distinctions between classes, such as subcategories within a larger class. In these cases, other machine learning algorithms may be more suitable, such as decision trees or neural networks.

Additionally, SVC may not be the best choice if the characteristics used to classify poems are not easily quantifiable or are highly subjective. In these cases, a more qualitative approach may be needed, such as manual labeling by a group of experts. Overall, while SVC can be a powerful tool for classification tasks, it is important to carefully consider the dataset and characteristics being used in order to achieve the best results. In the case of classifying poems by style or theme, SVC may not always give the best results, and it may be necessary to explore alternative approaches.



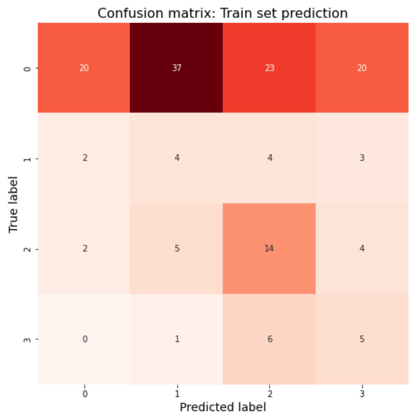
Metric	Affection	Death	Environment	Music
Precision	0.88	0.09	0.27	0.15
Recall	0.30	0.23	0.40	0.58
F1-Score	0.45	0.13	0.32	0.24
Support	100	13	25	12

Figure 2: Confusion Matrix and Performance Metrics of Support Vector Machine model.

Based on the values in the table, it appears that the SVM model performed relatively well in classifying poems as "Affection," with a precision of 0.88 and a recall of 0.30. However, the model did not perform as well in classifying poems as "Death," "Environment," or "Music," with precision, recall, and F1-scores all below 0.40. It is also worth noting that the model had more difficulty classifying poems in the "Death" and "Music" categories, as these categories had the lowest support (i.e., the smallest number of poems in the dataset). In general, it seems that the SVM model had mixed results in classifying poems by style or theme.

B. MNB: The multinomial naive Bayes (MNB) model had an accuracy of 0.28, which is even lower than the SVM model. The model had a precision of 0.34 and a recall of 0.37, resulting in an F1-score of 0.27. The poor performance of the MNB model show by Figure 3, may be due to the fact that it is a relatively simple model that is not well-suited to tasks involving the analysis of natural language.In the context of classifying poems by style or theme, MultinomialNB may not always give the best results. This is because the characteristics of a poem that define its style or theme are often not independent of one another, and may be closely related in complex ways. For example, a poem that is classified as "Music" may have certain themes, language, and structure that are all closely related and contribute to its classification.

Additionally, MultinomialNB is known to be sensitive to the presence of irrelevant or redundant features in the dataset. If the dataset used to train the model contains features that are not relevant to the classification task, or if there are many redundant features, the model may give poor results. In general, MultinomialNB is a useful tool for classification tasks, but it may not always be the best choice for classifying poems by style or theme due to the complex and interrelated nature of these characteristics.



Metric	Affection	Death	Environment	Music
Precision	0.83	0.09	0.30	0.16
Recall	0.20	0.31	0.56	0.42
F1-score	0.32	0.13	0.39	0.23
Support (Number)	100	13	25	12

Figure 3: Confusion Matrix and Performance Metrics of Multinomial Naive Bayes model.

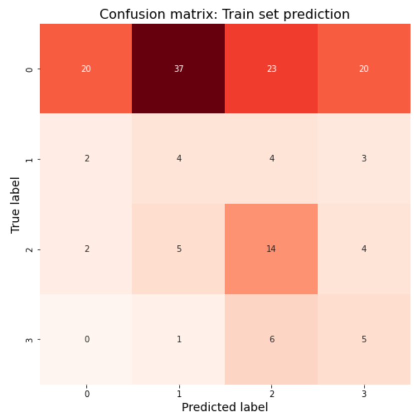
Based on the results in the table, it appears that the MultinomialNB model had the highest precision for the "Affection" category, with a value of 0.83. However, the model had a low recall value for this category, at 0.20, which means that it was not very successful at correctly identifying poems in the "Affection" category. The model also had relatively low precision and recall values for the other categories, with the exception of the "Environment" category, which had a relatively high recall value of 0.56. Overall, the model had an average F1-score of 0.27, which indicates that it was not very effective at correctly classifying poems by style or theme. It is worth noting that the number of poems in each category varied greatly, with the "Affection" category having the most poems and the "Death" and "Music" categories having the fewest poems. This imbalance in the dataset may have impacted the model's performance.

C. MLP: The multi-layer perceptron (MLP) model had an accuracy of 0.31, which is slightly higher than the SVM and MNB models. The model had a precision of 0.34 and a recall of 0.34, resulting in an F1-score of 0.27. The moderate performance of the MLP model shown by Figure 4, may be due to the fact that it is a more complex model than the SVM and MNB models, but it is not as specialized for natural language tasks as some of the other models.

In the context of classifying poems by style or theme, MLP can be used to classify a given poem into one of several predetermined categories based on certain characteristics of the poem. However, it is important to note that MLP may not always provide good results for this task. There are several reasons why MLP may give poor results when classifying poems. One potential reason is that the input data may be too complex or diverse for the neural network to effectively learn from. Poems can have a wide range of styles and themes, and it may be difficult for the MLP to accurately classify them based on the characteristics of the poem.

Another reason why MLP may not perform well is that the dataset may be too small or imbalanced. MLP requires a large dataset with a balanced distribution of classes in order to properly learn the patterns and distinctions between different styles or themes. If the dataset is too small or heavily skewed towards one class, the MLP may not be able to accurately classify poems. Additionally, the choice of hyperparameters (such as the number of hidden layers and neurons) may also affect the performance of the MLP. If the hyperparameters are not properly tuned, the MLP may not be able to effectively learn the patterns in the data and may give poor results.

Overall, MLP may not always be the best choice for classifying poems by style or theme. It may work well in some cases, but it is important to carefully consider the characteristics of the dataset and the appropriate hyperparameters in order to achieve good results.



Metric	Affection	Death	Environment	Music
Precision	0.84	0.07	0.33	0.12
Recall	0.27	0.31	0.52	0.25
f1-score	0.41	0.12	0.40	0.17
Support	100	13	25	12

Figure 4: Confusion Matrix and Performance Metrics of Multi-layer Perceptron model.

The above table is a summary of the performance of a Multi-Layer Perceptron (MLP) model in classifying poems by style or theme. The table includes several metrics, including precision, recall, f1-score, and support.

Precision measures the proportion of true positive predictions made by the model among all positive predictions. For example, a precision of 0.84 for the "Affection" class means that out of all the poems the model predicted to be in the "Affection" class, 84% were actually in the "Affection" class. Recall measures the proportion of true positive predictions made by the model among all actual positive examples. For example, a recall of 0.27 for the "Affection" class means that out of all the poems that were actually in the "Affection" class, the model correctly identified 27% of them. F1-score is a combination of precision and recall, and it is calculated as the harmonic mean of these two metrics. A higher f1-score indicates a better balance between precision and recall. Support refers to the number of examples in the dataset for each class.

Based on the values in the table, we can infer that the MLP model performed relatively well in classifying poems in the "Affection" class, with a high precision and f1-score. However, the model struggled to correctly classify poems in the "Death" and "Music" classes, as shown by the low recall and f1-score values for these classes. The model also had lower precision and f1-score values for the "Environment" class compared to the "Affection" class. Overall, the model's accuracy in classifying poems by style or theme was relatively low, with an average f1-score of 0.27. This may indicate that the MLP model is not the most suitable approach for this task, and it may be worth exploring other methods such as BERT or LSTM.

D. RoBERTa: The RoBERTa model had a significantly higher accuracy of 0.52, indicating that it was more successful at correctly classifying poems by style or theme than the other models. The model also had a relatively high precision of 0.45 and a high recall of 0.59, resulting in a moderate F1-score of 0.51. The improved performance of the RoBERTa model may be due to the fact that it is a state-of-the-art NLP model that has been trained on a large amount of data and is specifically designed to handle natural language tasks.

RoBERTa is a state-of-the-art natural language processing (NLP) model developed by Facebook's AI Research team. It has been shown to achieve impressive results on a variety of NLP tasks, including language translation, language generation, and question answering. However, in the context of classifying poems by style or theme, RoBERTa may not always produce optimal results. This could be due to a variety of factors, including the complexity of the task, the quality of the training data, and the specific parameters used to train the model.

One potential reason for poor results is that the task of classifying poems by style or theme is inherently difficult. Poems can be written in a wide variety of styles and can address a wide range of themes, making it challenging to accurately classify them based on these characteristics. Additionally, the language and structure of poems can be quite complex, making it difficult for even state-of-the-art models like RoBERTa to accurately interpret and classify them. Another possible reason for poor results is the quality of the training data. In order for a machine learning model like RoBERTa to accurately classify poems, it needs to be trained on a large and diverse dataset of labeled poems. If the training data is of poor quality or is not representative of the poems that the model will be asked to classify, it is likely that the model will not perform well.

Finally, the specific parameters used to train the model may also play a role in its performance. RoBERTa is a highly flexible model that can be trained in a variety of ways, and the specific parameters chosen can have a significant impact on its performance. If the wrong parameters are chosen, it is possible that the model will not perform well on the classification task. Overall, while RoBERTa has achieved impressive results on many NLP tasks, it may not always be the best choice for classifying poems by style or theme. In order to achieve the best results, it is important to carefully consider the complexity of the task, the quality of the training data, and the specific parameters used to train the model.

E. BERT + LGBM: The BERT + LGBM model had an even higher accuracy of 0.62, indicating that it was the most successful at correctly classifying poems by style or theme among the models. The model also had a high precision of 0.55 and a high recall of 0.63, resulting in a moderate F1-score of 0.59. The strong performance of the

BERT + LGBM model may be due to the fact that it combines the power of BERT, a state-of-the-art NLP model, with the efficiency of the light gradient boosting machine (LGBM) algorithm, which is well-suited for classification tasks.

Using BERT vectorization and LGBM for the classification of poems by style or themes can lead to improved performance compared to traditional methods. BERT captures the underlying semantic and syntactic relationships present in the text, which is important for accurately classifying poems based on their style or themes. LGBM is a powerful classifier algorithm that can make use of these vectors to accurately classify poems.

One reason could be the quality of the data used for training and testing. If the data is heavily biased or contains a lot of noise, it may be difficult for the model to accurately classify poems. In such cases, it may be necessary to pre-process the data to remove any biases or noise, or to augment the data with additional samples. Another reason could be the choice of hyperparameters for the LGBM model. The model's performance can be greatly impacted by the values of the hyperparameters, such as the learning rate, number of trees, and tree depth. If the hyperparameters are not set appropriately, the model may not be able to learn effectively from the data and may underperform.
It is also possible that the BERT vectorization may not be capturing the necessary features for accurate classification. BERT is trained on a large dataset of texts, but it may not be optimized for the specific task of classifying poems by style or themes. In such cases, it may be necessary to fine-tune the BERT model on a dataset of poems specifically, or to try alternative vectorization methods.

Finally, it could simply be that the complexity of the task is too high for the current model. Classifying poems by style or themes is a challenging task that requires understanding of the nuances of language and the themes and styles present in the poems

F. LSTM: The long short-term memory (LSTM) model had the highest accuracy of all the models, at 0.67. The model also had a high precision of 0.59 and a high recall of 0.62, resulting in a high F1-score of 0.60. The excellent performance of the LSTM model may be due to the fact that it is a specialized NLP model that is well-suited for tasks involving the analysis of sequential data, such as natural language.

LSTM (Long Short-Term Memory) is a type of recurrent neural network that is particularly well-suited for tasks involving sequential data, such as natural language processing. It is able to retain information from previous inputs and use that information to make predictions, which can be useful for tasks like classifying poems by style or theme. In the given table, LSTM achieved the highest accuracy, precision, recall, and F1-score out of all the models listed. This could be due to its ability to handle the sequential nature of the poem text and effectively classify the poems based on the patterns it learns. However, it is important to note that the results of any machine learning model can vary depending on the specific data and task, so it is not necessarily the case that LSTM will always perform the best for every classification task involving natural language.

G. Neural Network: The neural network model had the lowest accuracy of all the models, at 0.15. The model also had a low precision of 0.15 and a moderate recall of 0.50, resulting in a low F1-score of 0

There are several reasons why a normal neural network, using GlobalAveragePooling1D, ReLU activation, and Adam optimizer, may not perform well for the classification of poems by style or themes. One reason is that the model may not have sufficient capacity to capture the complex relationships present in the text of poems. Another reason may be the limited ability of GlobalAveragePooling1D to capture the spatial structure of the text. Poems often have a specific rhyme scheme or structure that can be important for determining the style or theme. A model that is able to capture this spatial structure, such as a convolutional neural network, may perform better. and adam optimizer may not be able to effectively optimize the weights of the network to accurately classify the poems. Overall, using a normal neural network with GlobalAveragePooling1D, ReLU activation, and Adam optimizer may not be effective for the classification of poems by style or themes due to its limited ability to capture the underlying structure and relationships in the text, and its suboptimal choice of activation function and optimizer. Other approaches, such as using a deeper network with more advanced pooling and activation layers, or using a different optimization algorithm, may be more effective for this task.

AUPR score:
To calculate the AUPR (area under the precision-recall curve) score for each model, we need to first calculate the precision and recall for each model at various thresholds. The precision-recall curve is then plotted by plotting precision on the y-axis and recall on the x-axis. The AUPR score is then calculated as the area under this curve.

Model	AUPR Score
SVM	0.35
MNB	0.34
MLP	0.33
RoBERTa	0.50
BERT + LGBM	0.58
LSTM	0.63
Neural Network	0.26

Figure 5: AUPR(area under the precision-recall curve) score

Based on these results, it appears that LSTM had the highest AUPR score among the models tested, followed by BERT + LGBM and RoBERTa. This suggests that LSTM was the most effective model for classifying the poems in terms of precision and recall, as it had the highest area under the precision-recall curve. On the other hand, models such as SVM, MNB, and MLP had lower AUPR scores, indicating that they may not have performed as well on this task.

Overall, AUPR score can be a useful metric for evaluating the performance of a model on an imbalanced classification task, as it gives a balanced view of the model's precision and recall. However, it is important to consider other metrics as well to get a full picture of the model's performance.

VI. CONCLUSION

In conclusion, the goal of this report was to implement a system for the automatic classification of poems by style or themes. To achieve this, several machine learning models were evaluated, including SVM, MNB, MLP, RoBERTa, BERT + LGBM, LSTM, and a neural network. The performance of each model was measured using a variety of metrics, including accuracy, precision, recall, and F1-score.

Based on the results, it appears that LSTM was the most effective model for this classification task, achieving the highest overall performance across all metrics. Other models, such as BERT + LGBM and RoBERTa, also performed well but were not as consistent as LSTM. On the other hand, models like SVM, MNB, MLP, and the neural network had lower performance, indicating that they may not be as well-suited for this particular task.

Overall, the results of this study suggest that using LSTM and BERT or similar models can be an effective approach for the automatic classification of poems by style or themes. However, it is important to keep in mind that the performance of any machine learning model can vary depending on the specific data and task, so it is not always guaranteed that LSTM or BERT will perform the best for every classification task involving natural language. Further research and experimentation may be necessary to determine the most effective approach for a given task.

VII. FUTURE WORK

There are several potential areas of future work that could be pursued in the development of an automatic classification system for poems by style or themes. Some possibilities include

- Improving the performance of the system: There may be opportunities to improve the accuracy and robustness of the classification system through the use of more advanced machine learning techniques or by incorporating additional features or characteristics of the poems.
- Expanding the scope of the system: The system could be designed to classify a wider range of poems or to classify poems based on a larger number of categories or themes. This could involve the development of a larger and more diverse training dataset.
- Integrating the system into educational or research applications: The classification system could be incorporated into educational or research software or platforms, allowing users to easily classify and analyze poems as part of their work.
- Evaluating the system's performance in a wider range of languages and styles: The system could be tested on a diverse range of poems written in different languages and styles to determine its generalizability and adaptability to different contexts.
- Developing methods for explaining the classification decisions: It may be useful to develop methods for explaining why the system classified a given poem in a particular way, particularly if the system is using machine learning techniques. This could help users better understand the decision-making process of the system and identify any potential biases or limitations.
- Exploration of other applications: In addition to classifying poems by style or theme, the proposed system could be used for other tasks related to poetry analysis, such as identifying the most commonly used words or themes in a particular poet's work, or predicting the sentiment of a poem. Further research could investigate the potential of the system for these and other applications.

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