A Deep Learning based Approach for Sindhi Poet Classification using Couplets

Abdul Samad
School of Science and Engineering
Habib University
Karachi, Pakistan
abdul.samad@sse.habib.edu.pk

Muhammad Munawwar Anwar *
Department of Computer Science
Emory University
Atlanta, Georgia
muhammad.munawwar.anwar@emory.edu

Ronit Kumar Kataria
School of Science and Engineering
Habib University
Karachi, Pakistan
rk06451@st.habib.edu.pk

Muhammad Murtaza
School of Science and Engineering
Habib University
Karachi, Pakistan
mm06369@st.habib.edu.pk

Faraz Ali
School of Science and Engineering
Habib University
Karachi, Pakistan
fa06396@st.habib.edu.pk

***Abstract*—Sindhi poetry serves as a monument to the cultural richness of Sindhi heritage, encompassing themes of affection, dedication, and community harmony. However, the contemporary decline in Sindhi language usage calls for innovative preservation efforts. In this study, we present a Deep Learning-based model for the automatic classification of Sindhi poets based on couplets. The dataset consists of 3000 couplets authored by five well-known Sindhi poets, each representing distinct periods and subject styles. We utilize PySpark's Word2Vec, a pre-trained BERT-based model called MuRIL, and Keras's Embedding Layer to produce sentence-level embeddings for each couplet. By doing extensive experiments and utilizing advanced approaches including Stochastic Gradient Descent, Random Forest, and 1D Convolutional Neural Networks, we have achieved a test accuracy of 87.2%. Our study is the first to focus on Sindhi poetry, as to the best of our knowledge, no prior work has been done in this field.**

I. Introduction

Sindhi culture is known for its rich and enduring legacy, which spans a millennia. The Sindhi language, a descendant of the Indo-Aryan languages, is the foundation of this cultural tradition. Sindhi poetry occupies an important place within this framework [19]. By employing a broad range of styles such as *Kafi*, *Vaee*, *Beit*, *Geets* and *Dohira*, Sindhi poetry has served as a powerful medium for expressing love, loss and devotion. These poems, often passed down through generations, offer unique insights about the Sindhi society's values. [20]

Sindhi literature is rich in poets who have had a long-standing impact on the cultural landscape. Foremost among these icons is Shah Abdul Latif Bhittai, regarded as the greatest Sindhi poet, whose book *Risalo* contains poems about love, devotion, and societal harmony [19]. Another poet who rose to prominence as a literary figure in the twentieth century was Sheikh Ayaz. Sheikh Ayaz uses poetry to explore the themes of social justice, human rights, and cultural identity [13]. These figures, along with many other poets such as Adal Soomro [24], Masroor Pirzada, and Ustad Bukhari [1], etc have left a lasting impression on Sindhi literature, with their diverse styles and thematic concerns adding to the richness and complexity of Sindhi poetry. [20]

While Sindhi culture has had a glorious past, it is currently facing multiple challenges. Factors such as rural to urban migration and the dominance of more widely spoken languages in popular culture have lead to a decline in the usage of Sindhi and the active participation in traditional practices. As a result, newer generations are less familiar with the richness of the Sindhi language and the diverse collection of Sindhi poetry. Consequently, there is a growing recognition of the need to preserve and promote Sindhi culture [6].

This paper aims to contribute positively in this direction by highlighting the work of famous Sindhi Poets and has two main contributions. The first contribution is a dataset containing 3000 Couplets by 5 Sindhi Poets. The second contribution is a Deep Learning based model for automatic identification of Sindhi Poets given a couplet. The remainder of this paper is structured as follows: Section II provides an overview of existing approaches for Poet classification in a variety of languages. Section III covers the details of our proposed methodology in depth, outlining the data preparation, feature extraction techniques, and the chosen machine learning and deep learning models. Section IV presents the experimental setup. Section V discusses the results obtained, analyzing the effectiveness of our approach. Finally, Section VI highlights the possible directions for extending this work in the future.

II. Literature Review

In their study, Tariq et al [23] presented machine learning-based models for identifying poets given a couplet in the Urdu language. Their dataset contained 3967 couplets from four different Urdu poets, gathered by scraping several Urdu poetry websites. First, the authors tokenized the dataset and

* This research was performed while the author was at Habib University.

extracted features using Term Document Frequency (TDF). Second, they selected features using Chi-Square and L1-Norm. Finally, they tested five different models: Naive Bayes, Decision Tree, Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Random Forest, both with and without feature selection. F1-Score, Precision, and Recall were used as evaluation criteria. The SVM model utilizing L1-Norm as a feature selection technique performed the best, with an F1-Score of 72%.

Similarly, Rao and Ahmed [14] compared different configurations for a poet attribution system given a couplet in the Urdu language. Their dataset consisted of 1,563 poems from five different poets, gathered by scraping various Urdu poetry websites. The authors tested four different models: SVM, LSTM, Naive Bayes, and DNN. Moreover, they also varied the number of lines in a poem, the n-gram used, and the size of training examples. Accuracy was used as the evaluation criterion. The SVM model with 10 lines per poem and a combination of unigram and bigram performed the best, achieving an accuracy of 88.77%.

Siddiqui et al. [22] presented a comparison of Deep Learning, Machine Learning, and Transformer-based models for identifying poets given a couplet in the Urdu language. Their dataset contained 18,472 couplets from 15 different poets, collected by scraping various Urdu websites. The authors used TF-IDF and Word Embedding as feature extraction techniques. After feature extraction, they tested a variety of models, including SVM, Logistic Regression, Naive Bayes, Random Forest, MLP, LSTM, GRU, CNN, BERT, and RoBERTa. Accuracy was used as the evaluation criterion. The BERT and RoBERTa models performed the best, achieving an accuracy of 80%.

Ruma et al. [16] presented Deep Learning based models for chronologically classifying Hafez's Persian poetry. Their dataset consists of 233 ghazals belonging to four different periods of time. First, the author pre-processed the dataset and extracted features using Distributed Memory Mean (DMM), Distributed Bag of Words (DBOW), and their combinations. Second, the authors tested three different models: GRU, LSTM, and BI-LSTM along with different feature extraction techniques. F1-Score, Precision, and Recall were used as evaluation criteria. LSTM model with DMM performed the best, achieving an accuracy of 85%.

Ekinci et al. [8] compared the effectiveness of Artificial Neural Networks (ANNs) and Deep Neural Networks (DNNs) in identifying poets based on poems written in the Turkish language. The dataset comprised 314 poems from five different poets, collected from various Turkish websites. Initially, the authors tokenized the dataset and extracted features using Term Frequency-Inverse Document Frequency (TF-IDF) and GloVe word embeddings. The TF-IDF features were used to train a Multi-Layer Perceptron (MLP), while the GloVe embeddings were utilized to train a Convolutional Neural Network (CNN). The performance of the models was evaluated using accuracy, precision, recall, and F1-score. The results indicated that the MLP outperformed the CNN, achieving an accuracy of 81%.

Zhu et al. [25] conducted a comparison of machine learning models for classifying the style of modern Chinese poetry. The dataset consisted of 836 poems in four different styles. First, the authors pre-processed the dataset by removing stop words and dividing each poem into words. Then, Doc2Vec was used to generate a vector embedding for each poem. Finally, the authors tested four different models: Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), Deep Neural Network (DNN), and Decision Tree (DT). Accuracy, F1-Score, Precision, and Recall were used as evaluation criteria. XGBoost performed the best, achieving an accuracy of 93.2%.

Shahriar et al. [21] conducted a comparison of deep learning models for classifying the emotions of classic Arabic poetry. The dataset consisted of 9452 poems with four different emotions, collected from different Arabic websites. The authors tested four different deep learning models: 1D-CNN, bidirectional RNN, CNN-LSTM, and the BERT transformer model. Accuracy, F1-Score, Precision, and Recall were used as evaluation criteria. The BERT model performed the best, achieving an accuracy of 76.5%.

Lastly, Mehta and Rajyagor [12] presented a deep learning approach for classifying emotions given a poem in the Gujarati language. Their dataset consisted of 315 poems categorized into nine different emotions as defined by *Navarasa*. First, the authors tokenized each poem into words. Second, they utilized Zipf's law to determine the likelihood of specific emotions within the provided poetry. The classification model achieved an accuracy of 87%.

III. Methodology

A. Dataset

Our dataset contains 3000 couplets from five distinguished poets: Shah Abdul Latif Bhittai, Sheikh Ayaz,Ustad Bukhari,Masroor Pirzada, and Adal Soomro, with 600 couplets of each poet. These poets were chosen because each of them represents a different era in history and focuses on different themes, enabling one to capture the diversity of Sindhi Poetry.

The dataset was obtained by web scrapping popular Sindhi Websites such as Sindhi Adabi Board (http://www.sindhiadabiboard.org/), Poet of Sindh (https://poetofsindh.blogspot.com/), and Sindhi Shayari (https://sindhishayari.blogspot.com/) using Python Library `BeautifulSoup`. The dataset contains about 12,507 unique words. The minimum number of words in a couplet was equal to 3 whereas the maximum number of words in a couplet was equal to 159. Since the average couplet length in our dataset was 17, we chose 17 as the length of our input sequence.

B. Embeddings

We employed three methods to generate sentence-level embeddings for each couplet. First, we used PySpark's Word2Vec model [1], which is pre-trained on a large Sindhi text corpus and provides 300-dimensional word embeddings. Each

[1]https://sparknlp.org/2022/03/16/w2v_cc_300d_sd_3_0.html

couplet was tokenized, and the resulting word embeddings were averaged to create a sentence embedding. The second method involved MuRIL, a BERT-based model trained on 17 Indian languages, including Sindhi, which generates 768-dimensional embeddings [10]. After tokenizing each couplet, the model produced contextualized word embeddings, which were averaged to obtain the sentence embedding. Finally, we used Keras's [2] Embedding layer within a sequential neural network architecture. This model converted input sequences into 300-dimensional dense vectors using an Embedding layer. The output was then flattened and passed through a Dense layer, yielding probabilities for five classes, with these dense embeddings serving as the sentence representation.

C. Machine Learning Techniques

In this paper, we utilized the following machine learning techniques to classify the poet given a couplet: Stochastic Gradient Descent (SGD), Random Forest, Extreme Gradient Boosting (XGBoost), and Softmax Regression.

Random Forest is an ensemble learning method that constructs multiple decision trees during training and selects the class based on the majority vote of the trees [2]. XGBoost, or Extreme Gradient Boosting, iteratively builds weak decision trees, each correcting the errors of the previous ones, to improve classification accuracy [4]. Softmax Regression assigns input data points to multiple classes by computing a linear combination of features and applying the Softmax function to generate probabilities for each class [3]. Lastly, SGD is an optimization algorithm that updates model parameters by estimating gradients using a minibatch or single data point, making it particularly effective for training neural networks [15].

D. Deep Learning Techniques

In this paper, we utilized the following deep learning techniques to classify poets based on couplets: Multilayer Perceptron (MLP), One-dimensional Convolutional Neural Network (1D-CNN), Bidirectional Gated Recurrent Unit (Bi-GRU), and Bidirectional Long Short-Term Memory (Bi-LSTM).

Multilayer Perceptron (MLP) consists of one input layer, three hidden layers, and an output layer. The dimensions of the input layer depend on the embedding used. The first hidden layer has 64 neurons, the second has 128 neurons, and the third has 192 neurons, all utilizing the ReLU activation function. The output layer uses the Softmax activation function [17].

Bidirectional Gated Recurrent Unit (Bi-GRU) includes one input layer, one bidirectional GRU layer, one dense layer, and an output layer. The dimensions of the input layer are determined by the embedding used. The bidirectional GRU layer has 128 neurons with Tanh activation. The dense layer has 128 neurons with ReLU activation. The output layer uses the Softmax activation function [5], [18].

Bidirectional Long Short-Term Memory (Bi-LSTM) features one input layer, one bidirectional LSTM layer, one dense layer, and an output layer. The input layer dimensions depend on the embedding used. The bidirectional LSTM layer consists of 128 neurons with Tanh activation. The dense layer has 128 neurons with ReLU activation. The output layer uses the Softmax activation function [9], [18].

One-dimensional Convolutional Neural Networks (1D-CNNs) are composed of one input layer, one 1D convolution layer, one 1D global average pooling layer, one dense layer, and an output layer. The input layer's dimensions depend on the embedding used. The 1D convolution layer applies 128 filters with a kernel size of 1 and uses ReLU activation. The dense layer has 128 neurons with ReLU activation, and the output layer utilizes the Softmax activation function [11].

E. Transformer Models

BERT (Bidirectional Encoder Representations from Transformers) is a Transformer-based model. It is trained with Masked Language Modeling (MLM), where 15% of words are replaced with a [MASK] token for prediction, and Next Sentence Prediction (NSP), where the model learns to determine if the second sentence in a pair follows the first in the original document. BERT's training involves minimizing the combined loss from both strategies. In this paper, we utilized MuRIL, a BERT model pre-trained on 17 Indian languages including Sindhi, for poet identification in the Sindhi language. MuRIL has variants, including Large and Base. However, we were only able to use the Base model, which has approximately 138 million parameters [7].

IV. Experimentation

A. Experimental Setup

We evaluated model performance using accuracy. The dataset was divided into 2160 samples for training, 600 for testing, and 240 for validation. Model training was performed on cloud platforms, specifically Google Colab with 12GB RAM and an NVIDIA Tesla T4 GPU, and Kaggle's Kernel with 29GB RAM and two NVIDIA Tesla T4 GPUs.

B. Machine Learning Models

For each different type of Embedding, we trained all the Machine Learning Models with the same hyper parameters. The hyper parameters used for the Machine Learning Models are summarised in the following table.

Model	Hyper Parameter	Value
Stochastic Gradient Descent	Max Iterations	1000
Softmax Regression	Max Iterations	1000
Random Forest	Number of Trees	100
Extreme Gradient Boosting	Number of Trees	100

TABLE I: Hyper parameters for Machine Learning Models

C. Deep Learning Models

For each different type of Embedding, we trained all the Deep Learning Models with the same hyper parameters. The hyper parameters used for the Deep Learning Models are summarised in the following table.

[2]https://keras.io/api/layers/core_layers/embedding/

Hyper Parameter	Value
Epochs	100
Batch Size	64
Learning Rate	0.001
Optimizer	Adam
Loss function	Cross Entropy Loss

TABLE II: Hyper Parameters for Deep Learning Models

D. Transformer Models

The hyper parameters used to fine tune MuRIL are summarised in the table III

Hyper Parameter	Value
Epochs	25
Train Batch Size Per Device	16
Validation Batch Size Per Device	8
Learning Rate	0.00005
Optimizer	Adam
Loss function	Cross Entropy Loss

TABLE III: Hyper parameter for fine tuning MuRIL

V. Results & Discussion

A. Machine Learning Models

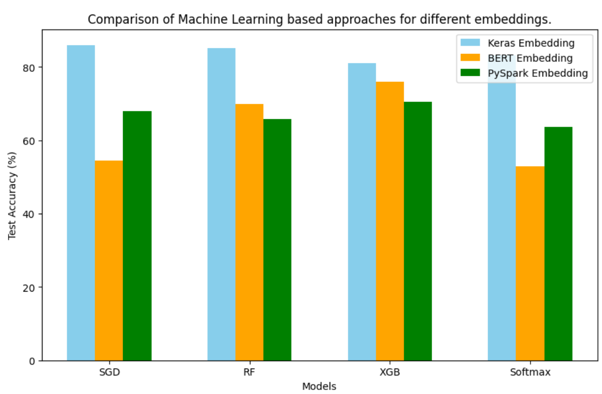

Fig. 1: Comparison of the performance of Machine Learning models on the test dataset using different embeddings.

The comparison of the Machine Learning models on the different embeddings can be viewed in Figure 1. In the figure, we can see that the highest performance was obtained on Keras embeddings followed by BERT embeddings and then PySpark embeddings. The best performance of 86% on the test dataset was obtained by Stochastic Gradient Descent on Keras Embedding.

B. Deep Learning Models

The comparison of the Deep Learning models on the different embeddings can be viewed in Figure 2. In the figure, we can see that the highest performance was obtained on Keras embeddings followed by BERT embeddings and then PySpark embeddings. The best performance of 87.2% on the test dataset

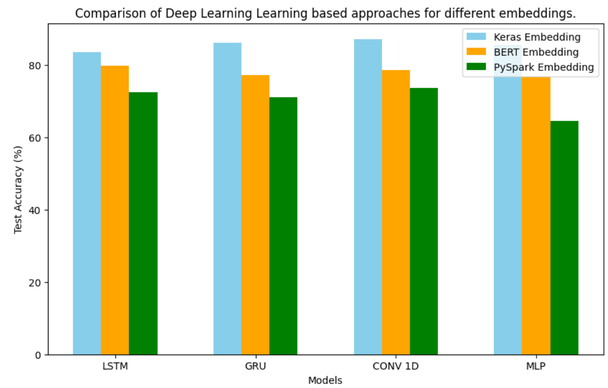

Fig. 2: Comparison of the performance of Deep Learning models on the test dataset using different embeddings.

was obtained by 1D Convolutional Neural Network on Keras embeddings.

C. Transformer Models

The performance of MuRIL after fine tuning is summarised in Table IV. In the table, we can see that fine tuning MuRIL has comparable performance to Machine Learning and Deep Learning models trained on different types of embeddings.

Dataset	Accuracy (%)
Train	99.3
Test	86
Validation	83.3

TABLE IV: Summary of the BERT model after fine tuning.

A plot of Cross Entropy Loss vs Epochs can be viewed in Figure 3. From the figure, we can see an overall trend of model over fitting. Initially, the training loss decreases sharply, while the validation loss decreases slightly and then starts to increase. As training progresses, the training loss continues to decrease and approaches zero, while the validation loss fluctuates and remains high. Since the other models also followed a similar trend, we have not included their Loss vs Epochs plots to avoid cluttering the paper.

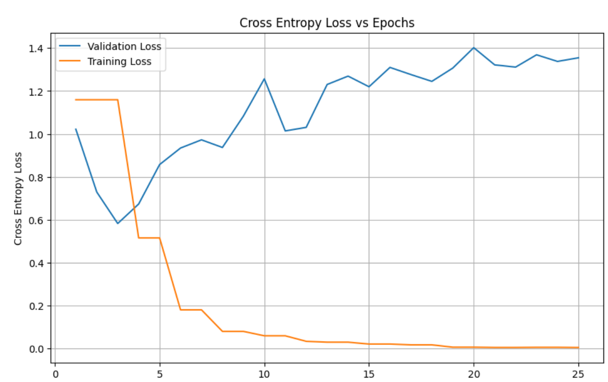

Fig. 3: Cross Entropy Loss vs Epochs while fine tuning MuRIL

Embedding	Keras Embedding			Bert Embedding			PySpark Embedding		
Model	Train	Validation	Test	Train	Validation	Test	Train	Validation	Test
SGD	99.3	82.5	86	56.4	55.8	54.5	74.8	65.4	68
Random Forest	99.9	80.8	85.2	99.8	71.3	70	99.8	63.3	65.8
XGBoost	99.8	80.4	81	99.8	77.1	76	99.9	70.4	70.6
Softmax Regression	98.5	79.1	83.3	57.5	57.9	53	66	60	63.7
LSTM	99.8	81.3	83.5	95.5	77.5	79.8	96	67	72.5
GRU	99.8	82.9	86.1	93.7	76.7	77.3	94	67	71
CONV 1D	99.8	83.3	87.2	94.6	77.5	78.7	99.8	71.6	73.6
MLP	99.9	84.2	85.5	93.7	75.8	76.8	67.4	61.7	64.5

TABLE V: The train, test, and validation accuracy for Machine Learning and Deep Learning model on all three embeddings.

The Confusion Matrices for the train, test, and validation dataset after fine tuning MuRIL can be seen in Figures 4, 5, and 6. In the confusion matrices for the test and validation dataset, we can that most miss-classifications are among Adil Soomro, Masroor Pirzada and Ustad Bukhari owing to their similar style and content of poetry. Since the other models also followed a similar trend, we have not included their Confusion Matrices to avoid cluttering the paper.

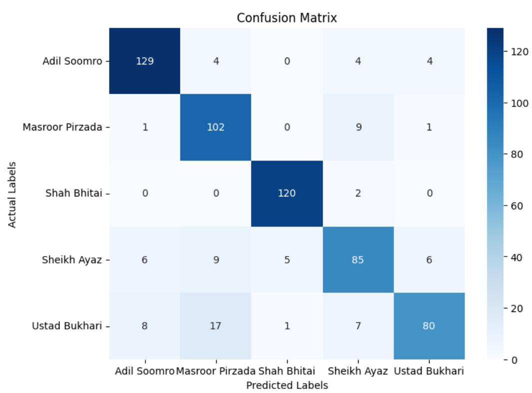

Fig. 4: Confusion Matrix for the Test Dataset

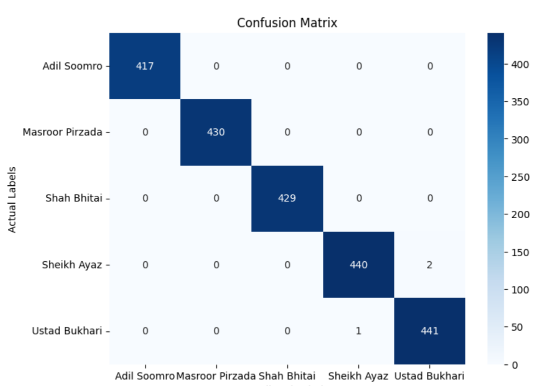

Fig. 5: Confusion Matrix for the Train Dataset

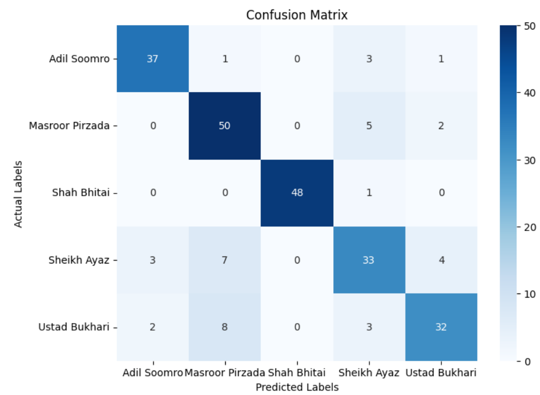

Fig. 6: Confusion Matrix for the Validation Dataset

D. *Comparison*

The performance of the Machine Learning and Deep Learning models on the train, test, and validation dataset for different types of embeddings has been summarised in Table V. After analysing these results, we identified some notable patterns.

1) Overall Trends: Generally, there is a significant disparity between high training accuracy and lower validation accuracy and test accuracy across many models indicating model over fitting.

2) Embedding Performance: Keras Embedding consistently yields a high training accuracy across all models; however, it also manifests substantial over fitting. In contrast, BERT Embedding, produces a lower training accuracy for models such as SGD and Softmax Regression, but demonstrates reasonably robust performance with Deep Learning models like LSTM and GRU. PySpark Embedding generally results in a lower training accuracy, yet models like LSTM and CONV 1D exhibit better generalization capabilities with this embedding.

3) Model Performance: Among all the models, LSTM and CONV 1D generally perform more effectively across different embeddings, which indicates their adaptability to various embedding techniques. Conversely, SGD and Softmax Regression show poor performance with BERT and PySpark embeddings. Although Random Forest and XGBoost achieve a high training accuracy, they are prone to over fitting across all embeddings.

VI. Future Work

This study faced several limitations that influenced our results and methodology. The primary issue was the lack of a comprehensive labeled dataset for Sindhi poetry. We created a dataset of 3,000 couplets from five poets using web scraping, but this approach was limited. Future work should focus on improving data acquisition by digitizing historical Sindhi textbooks to develop a more extensive and accurate dataset. Computational constraints also posed challenges, with free GPUs leading to timeouts and memory issues. Future research could address this by using more powerful cloud-based resources and optimizing model efficiency. Additionally, the small dataset size led to overfitting, which affected model generalization. To mitigate this, future efforts should include data augmentation, transfer learning, and semi-supervised learning techniques to enhance model performance and robustness. Future work could also explore the use of large language models (LLMs) to leverage their advanced capabilities for better performance and consider poetry generation techniques to create synthetic data and enrich the dataset.

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