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Author Profiling From Short Romanized Urdu Messages: A Preliminary Investigation Using Transfer Learning Models

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Abstract

Author profiling, a crucial task in natural language processing, involves identifying various attributes of an author, such as gender and age, from text. This study examines how transfer learning models in the context of author profiling from Roman Urdu text. We conduct experiments employing prominent models such as ELECTRA , BERT, RoBERTa, XLNet, Distil Bert, Distil RoBERTa,. Our analysis reveals superior performance in gender prediction using BERT, attaining an accuracy of 0.74698, precision of 0.7505, recall of 0.7462, and F1 score of 0.7456. On the other hand, RoBERTa demonstrates remarkable proficiency in age prediction with an accuracy of 0.8221, precision of 0.8215, recall of 0.8221, and F1 score of 0.8215. These findings showcase the effectiveness of transfer learning models in author profiling tasks offer insightful analysis for further research and applications in this domain.

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1 Introduction

Author profiling, a specialized domain within natural language processing, involves the analysis of written text to deduce various attributes of authors, such as gender and age. Understanding these attributes is pivotal for applications ranging from targeted advertising and content personalization to forensic linguistics. In the specific context of Roman Urdu, a language variant utilizing the Roman script for Urdu, author profiling presents unique challenges due to the distinct linguistic characteristics of this variant.

This study delves into the intricacies of author profiling in Roman Urdu text, employing advanced transfer learning models to predict the gender and age of authors. Transfer learning, a technique involving the use of pre-trained models on extensive datasets followed by fine-tuning for specific tasks, has shown significant promise in natural language processing. The selected models for this investigation encompass a variety of cutting-edge models, including ELECTRA , RoBERTa, Distil Bert, XLNet, Distil Roberta, and BERT.

To comprehensively evaluate the model's performance, a diverse and well-annotated dataset was utilized. Several measures, such as accuracy, precision, recall, and the F1 score, were used to evaluate the outcomes of a number of experiments. For gender classification, the BERT model exhibited the highest performance, achieving an accuracy of 0.74698, a precision of 0.7505, a recall of 0.7462, and an F1 score of 0.7456. On the other hand, in age classification, RoBERTa demonstrated superior accuracy at 0.8221, accompanied by a precision of 0.8215, a recall of 0.8221, and an F1 score of 0.8215.

In addition to presenting the results for gender and age classification, this study offers an in-depth analysis and comparison of each model's overall performance. The evaluation metrics provide a nuanced understanding of the strengths and weaknesses of each model, offering valuable insights to guide further advancements in author profiling from Roman Urdu text. Furthermore, the study highlights the importance of transfer learning in enhancing model performance for author profiling tasks, contributing to the growing body of knowledge in this domain. The findings of this research significantly enhance our understanding of author profiling in the unique context of Roman Urdu, shedding light on the potential and challenges in leveraging advanced natural language processing techniques for effective author profiling. Natural language processing has paid a lot of attention to author profiling, with research focusing on predicting author attributes like gender, age, and personality traits. Existing literature delves into the methods and models employed for author profiling, with a particular emphasis on the advancements and challenges in the domain of Roman Urdu. This section provides an in-depth review of the existing body of knowledge, offering a foundation for our research.

The results of the experiments are presented and analyzed in Results and Discussion section. Each model's performance in predicting gender and age for Roman Urdu text is thoroughly examined using performance metrics like accuracy, precision, recall, and F1 score. Comparative analyses and discussions of the outcomes shed light on the strengths and limitations of the models and offer directions for future research.

2 LITERATURE REVIEW

In recent years, the study of authorship verification, personality prediction, and author profiling has gained significant attention due to the increasing availability of digital text data and the applications it enables. This review synthesizes research across three major areas: linguistic profiling for author recognition and verification, personality prediction in social media, and gender prediction in author profiling. Additionally, it encompasses the evaluation of these techniques in the context of predicting user demographics and behavior based on linguistic patterns.The work by Halteren, H. Van[1] introduced a novel approach known as linguistic profiling for author recognition and verification. The study emphasizes the use of linguistic features to create text profiles that are then compared to average profiles for specific groups of texts. The research highlights the effectiveness of this technique for authorship verification, achieving a False Accept Rate of 8.1% and a 99.4% 2-way recognition accuracy using optimized parameter settings. The primary outcomes measured were False Accept Rate, False Reject Rate, and 2-Way Recognition Accuracy.Social media has become a crucial platform for users to share thoughts, opinions, and activities. Predicting personality traits from social media data is a growing area of interest. Lima, A.C.E [2] presented a unique approach by utilizing the Big Five personality model, transforming the problem into a multi-label classification task. The methodology involved the use of meta-attributes extracted from groups of texts, deviating from traditional single-text approaches. The study achieved an approximate 83% accurate prediction of personality traits. Outcomes focused on accuracy for personality prediction and classification rates for distinct personality traits.Author profiling involves predicting demographic characteristics such as gender, age, and more based on writing styles. Swathi, C[3] proposed a supervised term weight measure to improve gender prediction accuracy by assigning appropriate weights to terms. The study emphasized the significance of feature weight assignment in author profiling, achieving improved accuracy for gender prediction compared to existing approaches. Gender Prediction Accuracy was the primary outcome measured in this research.Furthermore, in the context of predicting user demographics and behavior, Patra, B.G [4] employed linguistic and stylistic patterns to predict authors' gender and age. The study achieved notable accuracy of '56.83%' for gender classification and '28.95%' for age group classification, emphasizing the effectiveness of automated author profiling.

Additionally, Giménez, M [5] proposed a methodology for author profiling using natural language processing and machine learning techniques, achieving an overall accuracy of 0.6857. This methodology focused on identifying demographic features, personality traits, gender, and age of authors from Twitter data in multiple languages.The studies reviewed indicate a trend toward leveraging linguistic features and advanced machine learning techniques for authorship verification, personality prediction, and author profiling. These approaches showcase the potential of linguistic analysis to predict diverse user attrbutes, providing valuable insights into user behavior and enabling a range of real-world applications.

The study presented by Peersman, C [6] addresses the need to monitor user profiles for false information on online social networks. The primary focus is on predicting age and gender through text analysis of chat texts. The research aims to contribute to enhancing online safety by flagging false profiles. It explores text categorization approaches, highlighting the challenge of nonstandard language variations in online communications. The outcomes revolve around predicting age and gender with insights into informative features for accurate predictions.In contrast, Nguyen, D [7] frame author age prediction as a regression problem, employing a linear regression model based on shallow text features. The study leverages diverse data genres, including blogs, telephone conversations, and online forum posts. It investigates joint and corpus-specific models using domain adaptation techniques. The research emphasizes effective stylistic and content-oriented features, achieving correlations up to 0.74 and demonstrating the potential of linguistic analysis in predicting author age.

The work by Alvarez-Carmona, M. A [8] focuses on author profiling, aiming to predict specific characteristics by analyzing written documents. The study emphasizes the relevance of content-based features and introduces a novel framework utilizing distributional term representations (DTRs). It conducts a comparative analysis of various DTRs, such as DOR, TCOR, SSR, and word2vec, highlighting their suitability for author profiling in social media domains. The outcomes underscore the competitive performance and interpretability of DTRs in this task. Lundeqvist, E [9] delve into the task of author profiling using a machine learning approach, aiming to detect gender, age, and native language of users in social media. The study compares two distinct approaches: one employing manually extracted features and another utilizing learning algorithms with raw data. The research emphasizes the efficiency of machine learning algorithms in author profiling, considering applications in crime investigations and other domains. The outcomes indicate the significance of dataset characteristics and algorithm hyperparameters for achieving optimal performance. These studies show how text analysis and machine learning can be used to predict different user demographics, such as age, gender, and profiling traits, in online situations. Each approach explores different aspects of the problem, ranging from feature extraction techniques to regression models and distributional term representations, providing valuable insights into this evolving field. The research paper by Pentel, A [10] stresses the use of text readability factors in place of conventional n-grams and focuses on automatic age detection using relatively short texts (about 100 words per author). Children and teenagers up to the age of 16 and adults aged 20 and older make up the two age groups that the research divides the training dataset into. Ten distinct models were constructed and evaluated using a variety of machine learning methods, including Logistic Regression, Support Vector Machines, C4.5, k-Nearest Neighbor, Naive

Bayes, and Adaboost.. The outcomes demonstrate the effectiveness of Support Vector Machine with Adaboost and Logistic Regression models, achieving high f-scores of 0.94 and 0.93, respectively. Bsir, B. R [11], the focus shifts to author profiling, particularly gender identification, using Long Short-Term Memory (LSTM) neural network architecture. The paper addresses the importance of author profiling in crime, marketing, and business domains. The Long Short-Term Memory neural network, known for mitigating the vanishing-gradient problem, is applied for gender identification. The experimental results indicate that the proposed LSTM neural network outperforms traditional machine learning methods in gender identification tasks.

The research presented by Weren, E.R [12] delves into authorship analysis, specifically classifying texts based on authors' stylistic choices to infer their age and gender. The study evaluates a wide range of features, spanning from Information Retrieval to Sentiment Analysis, to identify the most discriminative features. Experiments conducted on a substantial corpus of over 236K blogs demonstrate that Information Retrieval features are the most discriminative, surpassing state-of-the-art performance in age and gender prediction.These research works showcase the significance of employing various text analysis methodologies and machine learning algorithms to predict author demographics, particularly age and gender. From innovative feature selection like text readability features to advanced neural network architectures like LSTM, each study brings unique insights and advancements to the field of author profiling. The study outlined in Vashisth, P [13] addresses the rising popularity of content sharing on social media platforms by focusing on gender classification using Twitter text data. The project creates a gender classification system using tweets and natural language processing techniques. The Bag of Words (Term Frequency-Inverse Document Frequency), Word Embedding (W2Vec, GloVe), and more conventional machine learning approaches like Logistic Regression, Support Vector Machine, and Naive Bayes are among the various categorization algorithms that are compared. Since a regular public dataset of the needed volume wasn't available, a new dataset was created specifically for this inquiry. The study concludes that conventional Bag of Words models did not produce meaningful gender classification findings. However, when several machine learning strategies are paired with word embedding models, particularly W2Vec and GloVe, were very successful at identifying gender based on text from Twitter.

The study presented in Kiratsa, P. I [14] focuses on identifying the gender of Facebook profile owners through analysis of Facebook user profiles. The research applies a range of machine learning models to features extracted from users' Facebook profiles, primarily related to gender preferences. The study demonstrates that numerous features extracted from Facebook profiles can effectively aid in identifying the gender of profile owners. Machine learning techniques are shown to achieve a high accuracy of 97.30% in gender identification using a substantial amount of Facebook profile data.These studies highlight the effectiveness of NLP techniques and machine learning models in classifying gender based on social media text data. Utilizing features from various social media platforms, these approaches prove valuable in applications such as legal investigations, forensics, marketing analysis, advertising, and recommendation systems.The research in Lundeqvist, E [15] focuses on author profiling, aiming to detect gender, age, and native language using machine learning algorithms. Two alternative methods are contrasted: one uses Support Vector Machine and Feed-Forward Neural Networks to manually extract features, and the other uses Convolutional Neural Networks and Long Short-Term Memory to learn features from raw data.. The study demonstrates that manually extracted features yielded better results for author profiling, emphasizing the impact of dataset characteristics and hyperparameters on performance.The study of Holuba, S [16] explores grouping authors of printed text messages in social networks by applying machine learning of classifier models. The research confirms the possibility of grouping authors based on text message classification. The study utilizes machine learning models trained on message windows of 100 characters, demonstrating that authors with similar text content and form can be grouped effectively. The results have implications for identifying groups of authors engaged in joint activities in social networks. Alroobaea, R [17], the authors address the problem of author profiling, focusing on age and gender estimation based on textual productions. Support Vector Machines, Random Forest, Multilayer Perceptrons, Decision Trees, Naive Bayes, k-Nearest Neighbors, and Long Short-Term Memory (LSTM) are just a few of the machine learning techniques used in this work. Using the PAN-AP-2015 dataset from Twitter, the research shows that different machine learning techniques yield varying results depending on the dataset and its size. Deep learning techniques, particularly LSTM, prove to be effective when handling large datasets.Fatima, M [18] presents a study focused on creating a multilingual SMS-based author profiling corpus. This corpus encompasses 810 annotated participants, each characterized by gender, age, native language, native city, qualification, occupation, and personality type. The study uses content-based character 5-gram features and demonstrates the outperformance of this feature for gender identification. The corpus developed in this study serves as a valuable resource for evaluating various author profiling methods[19].

The study of Jiang, Z [20] proposes a Multi-Task learning framework for Author Profiling (MTAP) that shares a document modeling module across three author profiling tasks: age, gender, and job classification. The framework integrates hierarchical features obtained through CNN, LSTM, and topic modeling. The study demonstrates that MTAP achieves state-of-the-art performance in all three author profiling tasks, utilizing supervised deep neural networks and an unsupervised probabilistic generative model. These studies shed light on different strategies and techniques employed in author profiling, showcasing the importance of appropriate feature extraction, machine learning algorithms, and dataset characteristics for achieving accurate demographic predictions.

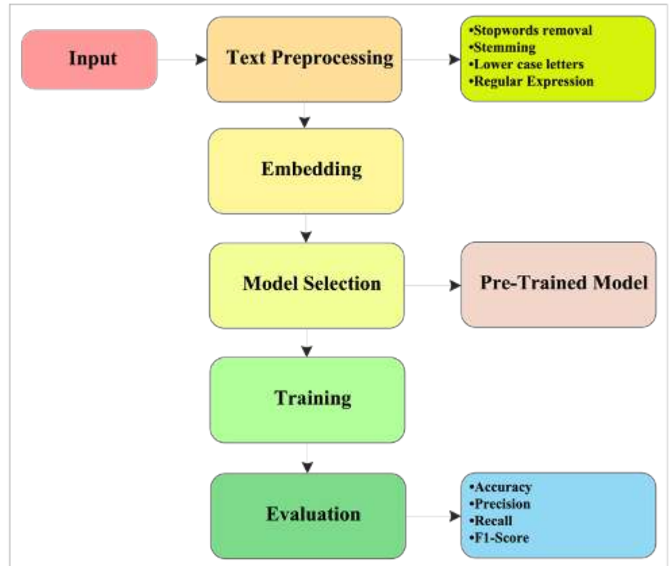

Figure 1. Research Methodology

3 RESEARCH METHODOLOGY

The research methodology employed in this study focuses on employing Transfer Learning models to enhance the author profiling process from Romanized Urdu text. Transfer Learning is a machine learning approach that utilizes knowledge acquired from a related task to improve performance in a different but related task, ultimately enhancing the accuracy and efficiency of author profiling. The methodology employed in the study is visualized in Figure 1 .

3.1 Text Preprocessing

Text preprocessing is a fundamental step in preparing textual data for thorough analysis and model training. In this process, the initial textual dataset, containing conversations from 407 individuals categorized by gender and age, undergoes a series of essential sub-steps. First, the text is tokenized, breaking it down into smaller units like words or subwords, which serve as the foundation for subsequent analysis. Stop words—common, low-information words such as "and" or "the"—are then removed to reduce noise and improve computational efficiency. Punctuation, special characters, and unwanted elements are also stripped from the text. Next, the words may undergo stemming or lemmatization, techniques that reduce them to their base or root form, aiding in linguistic

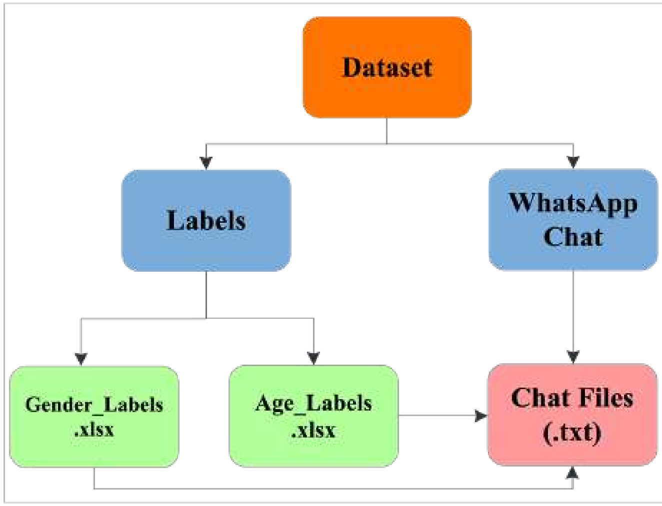

Figure 2. Dataset Structure

analysis. Lastly, any imbalances in the dataset, such as an unequal distribution of conversations across genders or age groups, are addressed to ensure fairness and unbiased model training. These preprocessing steps collectively ensure that the textual data is cleaned, standardized, and optimally structured, setting the stage for meaningful analysis and effective machine learning model training[21].Additionally, Figure 2 illustrates the composition and structure of the dataset, offering insights into its content and organization.

3.2 Embedding

The next stage is to convert the text into numerical vectors using a procedure called embedding after the textual data has undergone appropriate preprocessing. This transformation is essential for machine learning models to understand and process the text effectively. Given the diverse and intricate nature of our dataset, we opt for advanced models including ELECTRA, BERT, RoBERTa, XLNet, Distil Bert, Distil RoBERTa for this purpose. These models excel at creating embeddings that capture the rich context and nuanced meanings present in the text. By utilizing these models, we ensure that our embeddings are not only numerical representations but also encapsulate the depth and complexity of language[22], proving vital for achieving precise gender and age classification.

3.3 Model Selection

Opting for the appropriate model is pivotal to achieve accurate classification. In the context of gender and age classification, model selection is guided by their effectiveness in natural language processing and classification tasks. Specifically, BERT, known for its exceptional performance in various NLP tasks, demonstrates high accuracy for gender classification. On the other hand, RoBERTa, with its focus on enhancing BERT's pretraining methodology, exhibits superior performance and yields the best results for age classification. The strategic utilization of these models aligns with the specific nuances and requirements of our gender and age classification task, ensuring precise and effective outcomes.

3.4 Train Model

With the carefully selected models, the next step involves training them using the embedded data. Training encompasses the optimization of model parameters using labeled data, enabling the models to make accurate predictions. Each chosen model is trained to classify gender and age groups based on the embedded features derived from the previous step. To enhance the training process, we employ suitable training techniques, define appropriate loss functions to measure model performance, and utilize optimization algorithms to fine-tune the models[23]. In order to achieve optimal performance and make sure that the models can accurately categorize gender and age categories in the dataset, a rigorous training phase is essential. With the chosen models BERT and RoBERTa involves a dual-phase approach. Firstly, in the pretraining phase, both models employ transformer-based architectures to learn contextual embeddings from a vast pool of unlabeled text, understanding intricate language patterns and relationships. BERT's approach involves bidirectional encoding and prediction of masked words, as well as understanding sentence relationships. In Figure 3 RoBERTa optimizes this process by using a larger corpus and excluding the sentence prediction task, enhancing overall understanding. Subsequently, in the fine-tuning phase, the pretrained models are further tailored to the specific tasks of gender and age classification using labeled data.

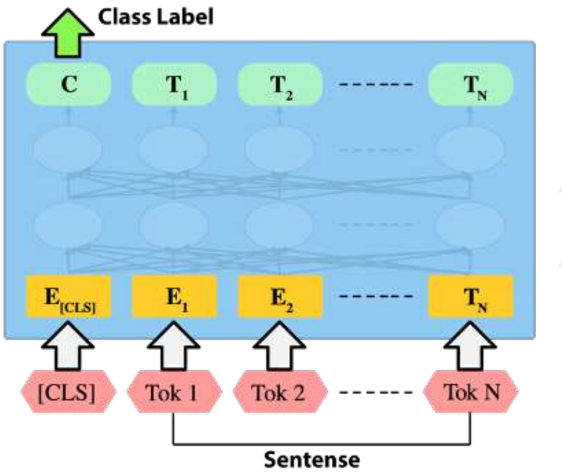

Figure 3. RoBERTa Model

This fine-tuning process involves adjusting millions of model parameters through backpropagation while minimizing task-specific loss functions, thus optimizing the models for precise gender and age group classification[24]. The nuanced understanding attained during pretraining, coupled with fine-tuning for task specificity, ensures that the models excel in accurately classifying gender and age groups based on the embedded features derived from the text.

$$p(y = i|x) = \frac{e^{(Z_i)}}{\sum_{j=1}^{k} e^{(z_j)}} \tag{1}$$

In Equation (1), $P(y = i \mid x)$ represents the conditional probability that the output (y) is i given the input (x). The numerator $e(Z_i)$ calculates the exponential of the logit (Z_i) associated with the i-th class. The denominator $\sum_{j=1}^{k} e(z_j)$ represents the sum of exponentials of logits for all k classes, from $j = 1$ to $j = k$. The equation normalizes these exponentiated logit values, providing a probability distribution over the classes.

3.5 Evaluation Metrics

In our pursuit of comprehensively assessing the performance of models for gender and age classification, we adopt a tailored set of fundamental evaluation metrics for each task. For gender classification, we emphasize accuracy, gauging the proportion of accurately classified gender instances and offering a holistic view of model performance. Precision, highlighting the model's exactness, quantifies the ratio of correctly predicted positive genders to the total predicted positives. Similarly, recall showcases the model's completeness, measuring the ratio of correctly predicted positive genders to the actual positives, ensuring all relevant instances are captured. Figures 4 and 5 display the Confusion Matrix and ROC Curves for Gender classification, respectively.

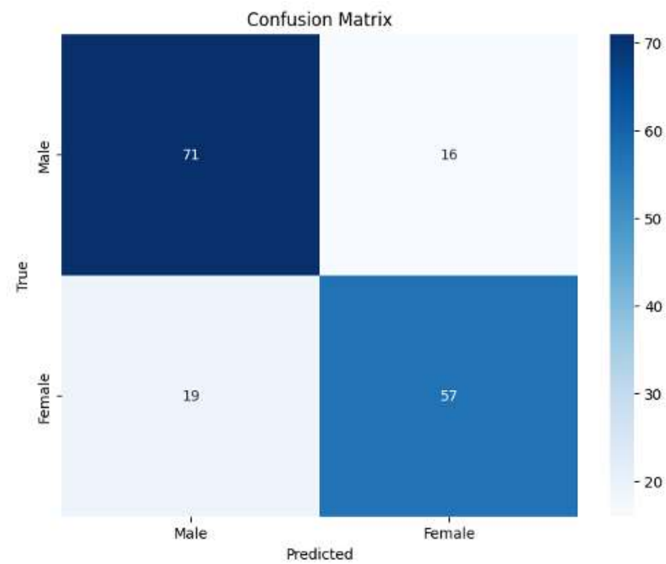

Figure 4. Confusion Matrix for Gender Classification

The F1-score, a harmonic mean of precision and recall, provides a balanced assessment of the model's accuracy and robustness in gender classification. This strategy also applies to age classification, where we assess the model's accuracy in categorizing age groups using accuracy, precision, recall, and F1-score. These evaluation metrics collectively provide a thorough understanding of the models' capabilities, guiding further refinements for optimal outcomes in gender and age classification tasks[25]. Moreover, in the realm of classification, the critical components of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) form the cornerstone of our evaluation metrics. The metrics, including accuracy, precision, recall, and the F1-score, utilize these components to offer useful information about the model's accuracy, precision, recall, and overall effectiveness, particularly crucial in dealing with imbalanced datasets. This holistic approach ensures a comprehensive evaluation of the model's performance across various classification tasks.

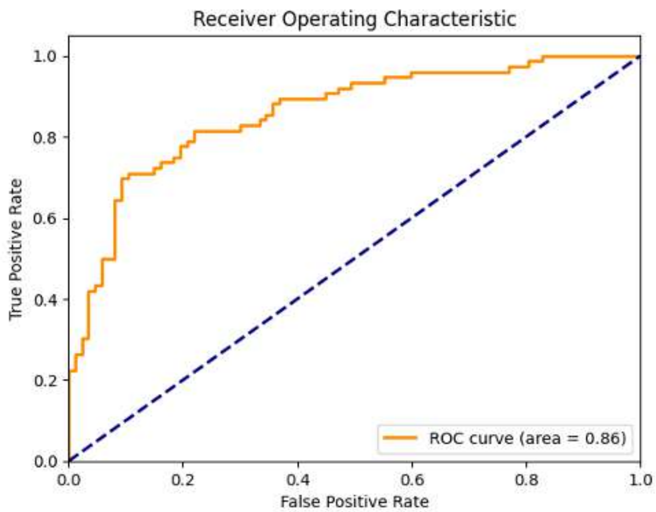

Figure 5. ROC Curves for Gender Classification

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
$$Precision = \frac{TP}{TP + FP}$$
$$Recall = \frac{TP}{TP + FN}$$
$$F1\text{-}Score = 2 \times \left(\frac{Precision \times Recall}{Precision + Recall}\right)$$

4 FINDINGS AND DISCOURSE

The findings of our study on author profiling for gender and age classification for Romanized Urdu utilizing multiple transfer learning models are shown and discussed in this section. The effectiveness of the XLNet, the RoBERTa Distil Bert, ELECTRA ,DistilRoberta, and BERT models was assessed. Accuracy, Precision, Recall, and F1-Score are among the evaluation measures. Table 1 presents the overall results for gender classification. Among the models, BERT demonstrates the highest accuracy of 74.56%. Then comes Distil Roberta with an accuracy of 66.26%. Electra-base and Electra-small also exhibit competitive accuracy at 60.24% and 55.53%, respectively. The F1-Score, a measure encompassing precision and recall, is highest for BERT, underscoring its robustness in gender classification. Table 2 presents the overall results for age classification.

Table 1. Overall Results for Gender Classification

Model	Accuracy	Precision	Recall	F1-Score
XLNet	56.62%	56.65%	56.6%	56.62%
RoBERTa	50.60%	25.30%	50%	33.59%
Distil-BERT	66.26%	66.57%	66.17%	66.02%
Distil-RoBERTa	66.26%	66.30%	66.28%	66.26%
ELECTRA-Base	60.24%	60.34%	60.16%	60.03%
ELECTRA-Small	56.62%	57.08%	56.44%	55.53%
Bert	**74.69%**	**75.05%**	**74.62%**	**74.56%**

Table 2. Overall Results for Age Classification

Model	Accuracy	Precision	Recall	F1-Score
XLNet	74.85%	74.89%	74.85%	74.82%
RoBERTa	**82.21%**	**82.15%**	**82.21%**	**82.15%**
Distil-BERT	72.39%	72.45%	72.39%	72.41%
Distil-RoBERTa	76.07%	76.35%	76.07%	76.10%
ELECTRA-Base	70.55%	71.48%	70.55%	70.72%
ELECTRA-Small	58.89%	59.55%	58.90%	56.05%
BERT	74.23%	74.04%	74.23%	74.03%

RoBERTa stands out with an accuracy of 82.21%, reflecting its superior performance in age classification. Notably, Distil Roberta also demonstrates strong performance with an accuracy of 76.07%. Similar to gender classification.Our results suggest that transfer learning models, particularly RoBERTa and BERT, exhibit promising capabilities in both gender and age classification. RoBERTa consistently shows high Accuracy values, indicating its effectiveness in capturing complex patterns related to age and gender. Distil Bert and Distil Roberta also present notable performance, making them efficient alternatives given their computational efficiency and comparable performance. The paper emphasizes how transfer learning models can be used for author profiling tasks. Fine-tuning these models for specific tasks can significantly enhance their predictive accuracy, enabling better understanding and analysis of author attributes from textual data. Further research could explore ensemble techniques or model combination strategies to leverage the strengths of different models for improved results. We visually depict our results for gender and age classification through graphical representations. Figure 6 presents the outcomes of our gender classification model, offering a clear view of the classification performance. Similarly, Figure 7 showcases the results of our age classification model, aiding in a comprehensive understanding of the predictions.

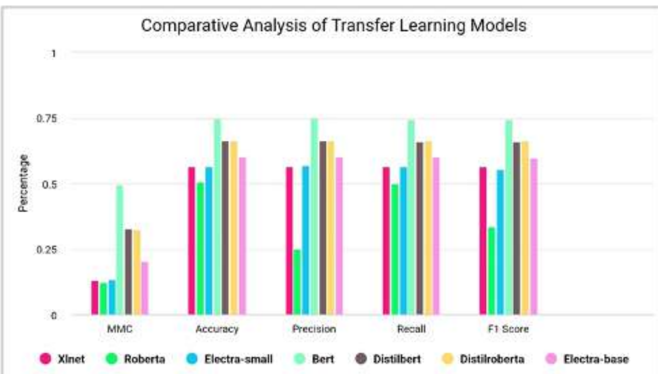

Figure 6. Gender Classification Visualization

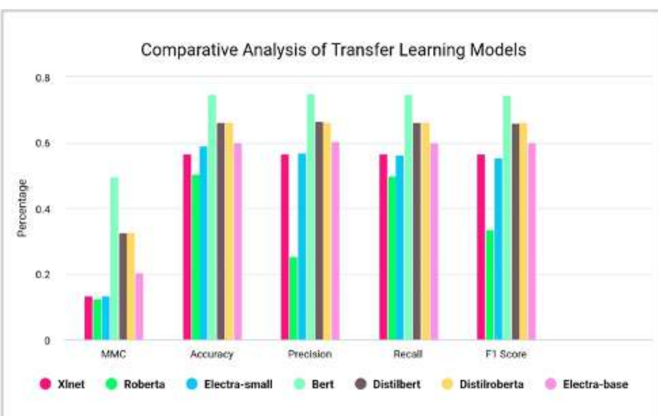

Figure 7. Age Classification Visualization

These graphical representations are essential tools, enabling a more intuitive interpretation of our findings and fostering a meaningful discussion regarding the efficacy and insights derived from our classification models.

5 CONCLUSION

In this study, we evaluated the use of various transfer learning models for author profiling, focusing on gender and age classification. The models evaluated included ELECTRA, RoBERTa, XLNet, Distil Bert, Distil RoBERTa , BERT. These models were employed to classify text data into predefined gender and age categories. Our results demonstrate the efficacy of these models in predicting gender and age from Roman Urdu textual data. BERT exhibited the highest accuracy in gender classification at 74.56%, while RoBERTa achieved the highest accuracy of 82.21% in age classification. Distil Roberta also displayed strong performance in both gender and age classification tasks. RoBERTa model showcased strong performance in on Romanized Urdu text to classify authors into different age classes (Child, Teen, and Adult) as presented in Tables 3. For the Child age class the model achieved an accuracy of 90.18% and an F1-score of 85.45%. In the Teen age class RoBERTa achieved an accuracy of 80.37% and an F1-score of 71.43%. Lastly, for the Adult age class the model achieved an accuracy of 88.96% and an F1-score of 82.69%. These results underscore the proficiency of the RoBERTa model in accurately profiling authors based on their age using Romanized Urdu text. The strong performance across different age groups demonstrates the potential of employing advanced natural language processing techniques for effective Author Profiling in the context of Romanized Urdu.

Table 3. Model Performance for Different Classes using RoBERTa

2*Model	2*Class	Accuracy	Precision	Recall	F1-score
3*RoBERTa	Child	90%	83%	87%	85%
	Teen	80%	75%	67%	71%
	Adult	88%	79%	86%	82%

The study underscores the potential of transfer learning models in understanding author profiles based on textual data. The versatility of these models allows for robust predictions across multiple demographic attributes. Furthermore, our findings emphasize the significance of model selection in achieving accurate predictions

6 LIMITATIONS AND FUTURE WORK

A primary limitation of this study is the small dataset used for training and testing in author profiling. The dataset size could potentially impact the generalizability of the findings to broader datasets and contexts within the field of author profiling for romanized urdu. To address this limitation, future research should emphasize enhancing the quality and diversity of the training data by incorporating a larger and more varied dataset specifically tailored to author profiling tasks. Additionally, another limitation is the evaluation of a limited number of models for romanized urdu author profiling. To overcome this limitation, researchers could explore ensemble methods and employ various transfer learning techniques to improve the performance of author profiling, ensuring a more comprehensive evaluation of different model architectures. Incorporating these integrations has the potential to substantially improve model accuracy and enhance generalizability for author profiling tasks.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

Author Contributions

Abid Ali: Methodology, Software, Experiments, Conceptualization, Visualization, Writing. **Dr. Muhammad Sohail Khan**: Supervision, Conceptualization, Methodology. **Muhammad Amin Khan**: Writing, Visualization, Reviewing and Editing.

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