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PSYCHOLOGICAL, EMOTIONAL, AND SENTIMENTAL ANALYSIS OF ANCIENT KANNADA INSCRIPTIONS EMPLOYING A MACHINE LEARNING APPROACH

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Abstract: The study of Kannada inscriptions has long focused on historical, linguistic, and cultural interpretations. However, the psychological dimensions embedded within these inscriptions have remained largely unexplored. In recent years, the integration of computational techniques, especially sentiment analysis has opened new possibilities for understanding the emotional and psychological undertones reflected in ancient writings. This approach forms a bridge between history, psychology, and digital linguistics, allowing researchers to interpret how rulers, poets, and scribes expressed emotions, intentions, and authority through language. Traditional epigraphy focuses on translation and interpretation, while sentiment analysis enables a deeper layer of psychological exploration. It helps to identify recurring emotional tones and assess how rulers used language to legitimize power, express gratitude, or evoke fear and loyalty among their subjects. This study introduces a computational approach to examine the emotional and psychological expressions found in Kannada inscriptions. To develop a methodological framework that integrates computational analysis with cultural and historical interpretation. The method applies a structured text processing pipeline, including cleaning, tokenization, and lemmatization, followed by TF–IDF feature extraction to represent linguistic patterns numerically. Multiple machine learning algorithms—such as Linear SVC, Logistic Regression, SGD Classifier, K-Nearest Neighbours, Multinomial Naive Bayes, and Random Forest were used to categorize the texts based on sentiment patterns. Among these, linear and ensemble models delivered the most consistent and accurate outcomes. Findings highlight that inscriptional language not only functioned as an administrative or religious tool but also as a vehicle for emotional expression, moral persuasion, and psychological influence in early South Indian society.
Keywords: Kannada inscriptions, historical linguistics, psychological interpretation, epigraphy.

1. INTRODUCTION:

Kannada inscriptions, found across southern India, serve as valuable records of political decrees, social customs, temple donations, and royal achievements. Beyond their administrative or religious content, these inscriptions also mirror the emotional state, worldview, and moral values of the time. By analysing the tone, vocabulary, and phrasing used in these inscriptions, scholars can infer the underlying sentiments such as pride, devotion, aggression, humility, or benevolence—that shaped royal communication and public expression. Inscriptions have long served as vital sources for reconstructing the social, political, and cultural histories of South India. Kannada inscriptions, in particular, document royal decrees, temple endowments, conquests, and charitable acts spanning from the early Kadamba period (4th century CE) to the Vijayanagara era (16th century CE). Traditionally, historians and philologists have analysed these inscriptions for factual information—dates, dynasties, and events—while largely overlooking the expressive and emotional layers inherent in their language.

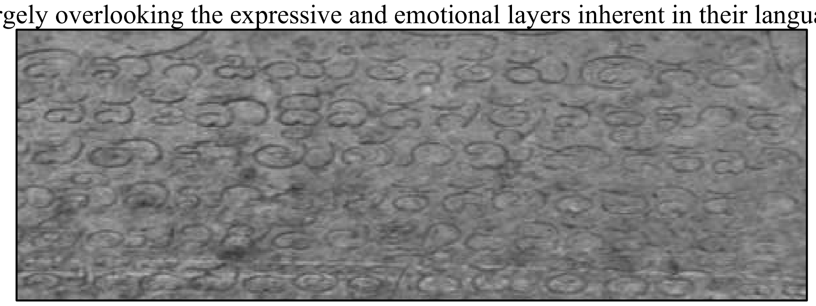

Fig. 1 Hoysala Kannada Inscription [1]

The picture represents an ancient Kannada inscription carved on a stone slab; a form of record widely used across southern India for more than a thousand years. Kannada inscriptions are among the richest sources for understanding the political, social, and cultural history of Karnataka. They preserve not only linguistic and artistic traditions but also reveal how people expressed authority, devotion, and everyday life through language and craftsmanship [2].

Recent advances in computational linguistics, especially sentiment analysis, have opened new possibilities for investigating how emotions and attitudes were articulated in historical texts. By applying these methods to Kannada inscriptions, scholars can trace patterns of emotional tone and rhetorical style across centuries, thereby gaining insights into how language reflected and shaped collective psychology. Analysing ancient inscriptions for psychological meaning requires careful contextualization. Sentiment scores alone cannot determine personality traits or internal emotions of historical figures. Instead, they represent the linguistic portrayal of power, piety, and emotion. Researchers must remain aware of cultural conventions, avoid anachronistic interpretations, and transparently communicate the limitations of computational inference.

2. SENTIMENT CLASSIFICATION TECHNIQUES

Sentiment classification methods can be broadly grouped into four categories: lexicon-based, machine learning, hybrid, and advanced approaches.

2.1 Lexicon-Based Approach:

This technique uses predefined sentiment dictionaries containing words tagged as positive, negative, or neutral. The dictionary-based method relies on lexical resources and may be expanded through synonym and antonym relationships, while the corpus-based approach derives sentiment polarity from large text corpora using word co-occurrence and contextual patterns.

2.2 Machine Learning Approach:

Machine learning models learn sentiment patterns from labeled data. Common algorithms include Decision Trees, Logistic Regression, Support Vector Machines, Naïve Bayes, and K-Nearest Neighbors. These models classify text based on statistical or probabilistic relationships among features.

2.3 Hybrid Approach:

Hybrid systems merge lexicon and machine learning principles to improve accuracy and contextual understanding. Techniques such as SVM, Neural Networks, Maximum Entropy, and Bayesian Networks balance rule-based precision with data-driven adaptability.

2.4 Other Approaches:

Modern sentiment analysis employs deep learning and transfer learning using pre-trained models like BERT and GPT. Methods such as RNN, CNN, LSTM, and Transformer architectures capture contextual and sequential dependencies, while aspect-based models focus on specific opinion targets for finer sentiment interpretation.

3. LITERATURE SURVEY

Sentiment analysis has become a significant research area within Natural Language Processing (NLP), focusing on the extraction and interpretation of emotions and opinions from text-based data. Early studies concentrated on rule-based and lexicon-driven models that depended on manually curated sentiment dictionaries and polarity terms. With advances in machine learning, these traditional methods were gradually replaced by statistical and supervised models capable of learning contextual meaning from text. While deep learning frameworks such as Convolutional Neural Networks (CNNs) and Transformer architectures have demonstrated high accuracy in modern NLP applications, their dependence on extensive datasets and computational resources restricts their suitability for smaller or domain-specific corpora. Consequently, traditional machine learning approaches remain an effective and interpretable solution for tasks involving limited or historical data.

Shankar et al. [3] explored machine-learning and ensemble algorithms on COVID-19–related Kannada data, demonstrating that ensemble approaches outperform individual models in managing unstructured social-media text. Sunita and Peter [4] applied supervised learning to semantic analysis of Kannada summaries, highlighting that meaning-level representation yields better emotional interpretation than keyword-based methods. Similarly, Chakravarthi et al. [5] created DravidianCodeMix, a dataset capturing code-mixed Kannada and other Dravidian languages, enabling multilingual sentiment and offensive-language identification. Kumar and Bhardwaj [6] compared major machine-learning algorithms for sentiment analysis in low-resource languages, concluding that linear and ensemble models provide the best trade-off between speed and accuracy. Kumar et al. [7] employed hybrid models to detect emotions in historical texts, validating their ability to capture subtle affective expressions. Sultana et al. [8] implemented sentiment analysis for product reviews using supervised classification algorithms. Their study highlighted how preprocessing techniques such as stop-word removal and stemming significantly enhance model accuracy for textual review data. AlQahtani [9] explored sentiment analysis for Amazon product reviews, employing both Naïve Bayes and Support Vector Machines to categorize consumer opinions effectively, emphasizing the importance of balanced datasets for precise polarity detection. Alabdulkarim et al. [10] analyzed social-media sentiments through machine-learning classifiers, illustrating that hybrid approaches outperform standalone models when dealing with multilingual and informal text structures. Bahtair [11] compared Naïve Bayes and Logistic Regression for marketplace reviews, concluding that logistic regression offers better adaptability to rating-based labelling schemes and noisy real-world data. Chetia et al. [12] examined public sentiment toward India's Union Budget 2023 using YouTube comments, demonstrating that online discourse analysis can uncover topic-specific public reactions through text mining. Medhat et al. [13] conducted a comprehensive survey on sentiment analysis algorithms, categorizing methods into machine-learning, lexicon-based, and hybrid approaches. Their work remains a cornerstone reference for understanding algorithmic evolution in opinion mining. Ahmad and Singla [14] evaluated sentiment analysis for Indian languages, stressing the necessity for corpus development and transfer learning to overcome linguistic diversity and resource scarcity. Ashbaugh and Zhang [15] compared traditional machine-learning and deep-learning architectures on customer reviews, finding that LSTM and CNN models outperform classical classifiers in detecting contextual sentiment. Chanda et al. [16] developed a sentiment analysis framework for code-mixed Dravidian languages using pretrained models and word-level language tagging, effectively handling multilingual noise and improving classification precision. Ijeri and Patil [17] presented a comparative evaluation of multiple machine learning algorithms for multi-emotion sentiment detection in Kannada, demonstrating that ensemble-based methods outperform traditional classifiers in recognizing subtle emotional cues. Kumar and Khanna [18] explored deep learning architectures for sentiment analysis in Malayalam, Tamil, and Kannada, highlighting the effectiveness of CNN-LSTM hybrids in extracting semantic features from under-resourced corpora. Hande et al. [19] benchmarked multi-task learning models for sentiment and offensive language identification across Dravidian languages, emphasizing the advantages of shared representations in low-resource conditions. Similarly, Phani et al. [20] focused on multilingual sentiment classification for Indian tweets, showing that cross-lingual features improve generalization for languages with limited annotated data. Roy and Kumar [21] designed an ontology-based approach for Kannada movie reviews, integrating semantic hierarchies to enhance contextual interpretation of sentiment-laden words. Kurian and Bhatia [22] employed transfer learning to boost sentiment analysis performance in South Indian languages, proving that pretrained embeddings from resource-rich languages can be effectively fine-tuned for regional ones. Eshwarappa and Shivasubramanyan [23] developed a novel dataset and part-of-speech tagging framework that enhanced feature extraction for Kannada text, improving sentiment classification reliability.

4 . METHODOLGY

4.1 Data Collection

The dataset for this study was derived from a curated corpus of Kannada inscriptions representing a variety of historical and cultural contexts. The data for the Kannada inscriptions was compiled from published epigraphic volumes, museum archives, digital repositories, and prepared by the researcher. The corpus comprises more than 1500 Kannada inscriptions sentences are used. Each inscription was digitized and segmented into individual sentences to enable sentence-level sentiment classification. The corpus was divided into training and testing subsets to ensure unbiased evaluation of model performance.

4.2 Data Preprocessing: Text data was cleaned and standardized through tokenization, removal of punctuation and numerals, normalization of spelling variations, and elimination of stop words. Lemmatization was applied to preserve meaningful linguistic structures while reducing redundancy.

4.3 Feature Extraction: A TF–IDF representation was used to convert text into numerical vectors, assigning higher weights to sentiment-bearing words. This approach enabled the models to identify key emotional and contextual patterns in the text.

4.4 Model Development: Six classifiers—SGD, Linear SVC, Random Forest, Logistic Regression, Multinomial Naive Bayes, and KNN—were trained for sentiment classification. Linear models were chosen for their ability to manage high-dimensional data, while Random Forest captured non-linear linguistic variations. Logistic and probabilistic models served as benchmarks, and KNN was used for comparison.

4.5 Model Training and Evaluation: Models were trained using scikit-learn in Python. Accuracy was used as the key metric. The SGD Classifier achieved the highest accuracy (96.47%), followed by Linear SVC (95.19%) and Random Forest (94.55%). Logistic Regression and Naive Bayes performed moderately, while KNN showed poor adaptability to textual data.

4.6 Rationale and Implementation: Linear and ensemble models excelled due to their scalability and strong generalization in sparse feature spaces. KNN's distance-based nature limited its contextual sensitivity. The workflow—from preprocessing to evaluation—was executed in a controlled Python environment, ensuring consistency and reproducibility across all models.

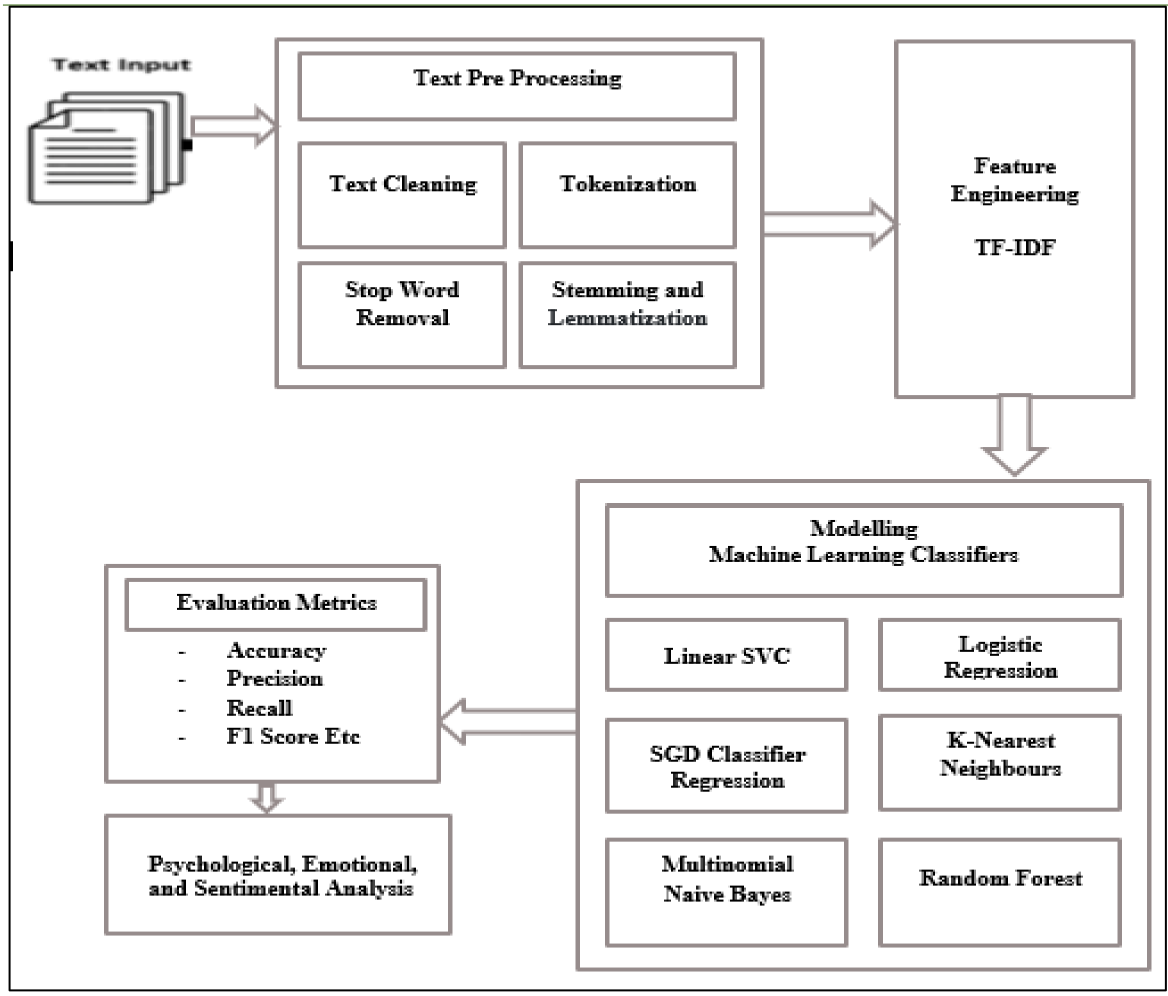

Fig.2 Steps to perform Psychological, Emotional and Sentimental Analysis

5. RESULTS AND ANALYSIS

Psychological, sentimental, and emotional analyses together uncover how Kannada inscriptions functioned not just as records of events but as expressive, emotive, and persuasive instruments. They expose the human dimension of epigraphy — the feelings, intentions, and psychological narratives woven into stone.

5.1 Psychological Analysis

Psychological analysis examines how the language of inscriptions reveals the mindset, motivations, and intentions of historical figures particularly rulers, poets, and scribes.

- Inscriptions were not merely administrative records; they were tools of influence and persuasion.
- For example, *War* inscriptions (the most frequent category) often demonstrate psychological strategies of power — glorifying victories, legitimizing rule, or instilling fear and loyalty.
- *Devotion* and *Donative* inscriptions reflect altruism, reverence, and social responsibility, showing how rulers or patrons sought emotional and moral legitimacy.

Thus, psychological analysis explores how inscriptions were crafted to shape the emotions and thoughts of their audience functioning as instruments of governance and social control through language.

5.2 Sentimental Analysis

Sentimental analysis identifies dominant emotional tones or attitudes embedded in inscriptional texts.

- Using computational methods (like sentiment scoring), inscriptions are categorized into emotional domains such as *Devotion*, *War*, *Culture*, etc.
- The prevalence of the *War* and *Culture* categories indicates that the inscriptions frequently blend heroic sentiment with cultural pride.
- This reveals a deep emotional engagement with valor, legacy, and identity — key components of medieval Kannada political and cultural consciousness.

Hence, sentimental analysis bridges linguistic data and emotional meaning, showing how language conveys sentiment across centuries.

5.3 Emotional Analysis

Emotional analysis focuses on specific emotions — such as pride, fear, devotion, or gratitude — expressed or evoked through inscriptional language.

- *War* inscriptions may express valor, aggression, pride, or triumph.
- *Devotion* reflects faith, humility, and reverence.
- *Culture* embodies aesthetic appreciation and communal identity.
- *Eulogistic* inscriptions often display admiration and respect, celebrating individuals or divine figures.

By examining the emotional spectrum within these texts, researchers can better understand how ancient societies encoded emotions into public communication, revealing collective psychology and social values.

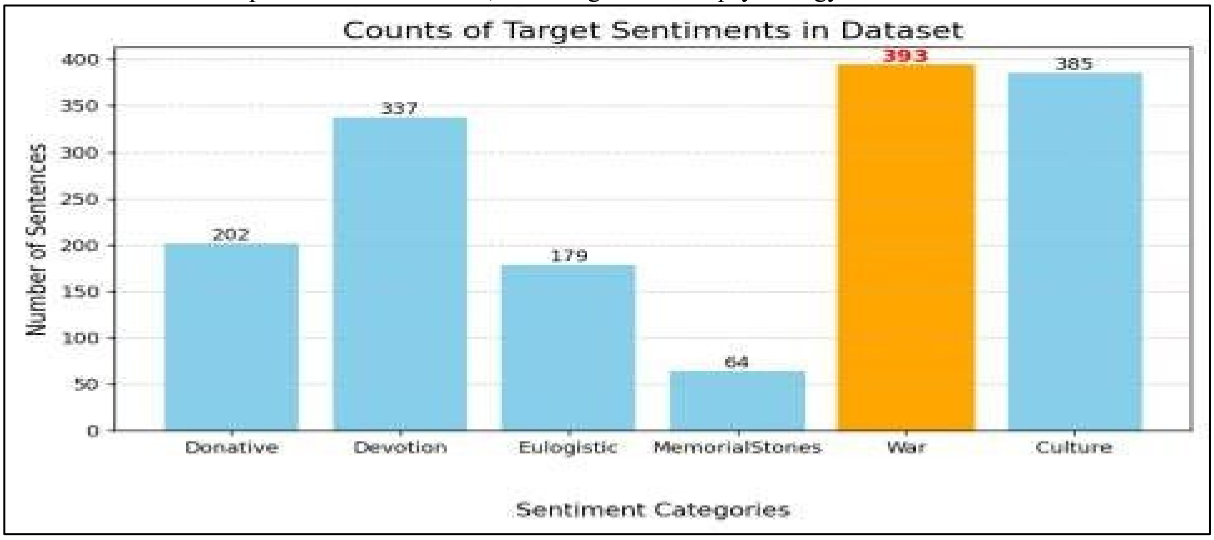

Fig 3. Counts of Sentiment Categories

In the below table 1, it summarizes how many sentences in a dataset are classified under each *target sentiment category*. Each category represents a specific emotional or thematic focus found in the text.

- Donative (202): Sentences that express generosity, donation, or giving.
- Devotion (337): Sentences showing religious faith, loyalty, or reverence.
- Eulogistic (179): Sentences containing praise or admiration for people, places, or events.
- Memorial Stones (64): Sentences referring to commemorative inscriptions or monuments.
- War (393): Sentences related to conflict, battles, or military themes.
- Culture (385): Sentences expressing cultural values, traditions, or heritage.

Table 1. Sentence Counts for Each Target Sentiment

Sl.No	Sentimental Categories	Count
01	Donative	202
02	Devotion	337
03	Eulogistic	179
04	Memorial Stones	64
05	War	393
06	Culture	385

Kannada Inscription Sentence: ಬಲ್ಲಾಳನು ಶತ್ರು ರಾಜ್ಯಗಳ ಸೇನೆಗಳನ್ನು ಗೆಲ್ಲಲು ದಿಟ್ಟತನದಿಂದ ಬಡಿಯುತ್ತಿದ್ದನು.

Table 2. Predictions from each Model

Sl.No	Classifiers	Predictions
01	Linear SVC	War
02	Logistic Regression	War
03	SGD Classifier	War
04	K-Nearest Neighbors	War
05	Multinomial Naive Bayes	War
06	Random Forest	War

Table 3. Sentiment counts across all the Models:

Sl.No	Sentimental Categories	Count
01	Donative	00

02	Devotion	00
03	Eulogistic	00
04	Memorial Stones	00
05	War	06
06	Culture	00

Table 3. shows how different emotional categories appear when the dataset is analysed through various computational models. Each category reflects a type of sentiment that might be expressed in an inscription, such as generosity, devotion, praise, remembrance, war, or culture. In this analysis, only the "War" category has been identified, with a total count of six, while all other categories record zero. This means that across all models, the language patterns and emotional cues in the examined text consistently point toward themes of conflict and power. This result highlights the inscription's focus on martial emotions such as courage, dominance, and victory, rather than softer or spiritual feelings like devotion or generosity. From a psychological point of view, such expressions often reflect the mindset of rulers who sought to assert authority and inspire loyalty among their followers.

Table 4. Accuracy from Various Classifiers

Sl.No	**Classifiers**	**Accuracy in %**
01	Linear SVC	95.19
02	Logistic Regression	83.01
03	SGD Classifier	96.47
04	K-Nearest Neighbors	32.69
05	Multinomial Naive Bayes	78.21
06	Random Forest	94.55

The table 4. lists the accuracy levels achieved by different machine learning models used for sentiment classification. Accuracy represents how correctly each model identified the target sentiment categories from the given dataset. Among the models tested, the SGD Classifier achieved the highest accuracy at 96.47%, showing it performed best in learning and predicting the emotional patterns in the inscriptional data. The Linear SVC model also performed very well with 95.19% accuracy, followed closely by the Random Forest classifier at 94.55%. These results indicate that models based on linear decision boundaries and ensemble methods are particularly effective for this type of textual data. On the other hand, Logistic Regression and Multinomial Naive Bayes produced moderate results with 83.01% and 78.21%, respectively. This suggests that while they capture general sentiment trends, they may struggle with more complex linguistic or emotional expressions. The K-Nearest Neighbors (KNN) model showed the lowest accuracy of 32.69%, implying it is less suited for handling large text-based features due to its reliance on proximity rather than learned decision boundaries. In summary, the comparison demonstrates that SGD Classifier, Linear SVC, and Random Forest are the most reliable models for sentiment analysis of Kannada inscriptions, while KNN is the least effective.

Table. 5 Precision

Sl.No	Classifiers	Culture	Devotion	Donative	Eulogistic	Memorial Stones	War
01	Linear SVC	1.00	0.89	0.91	1.00	1.00	0.97
02	Logistic Regression	0.77	0.82	0.88	0.87	0.70	0.79
03	SGD Classifier	0.93	0.92	1.00	1.00	1.00	0.79
04	K-Nearest Neighbors	0.30	0.26	0.31	0.00	0.00	0.79
05	Multinomial Naive Bayes	0.76	0.78	0.81	0.82	0.27	0.79
06	Random Forest	0.94	0.95	0.89	1.00	1.00	0.79

Table. 6 F1 Score

Sl.No	Classifiers	Culture	Devotion	Donative	Eulogistic	Memorial Stones	War
01	Linear SVC	0.94	0.91	0.95	1.00	1.00	0.79
02	Logistic Regression	0.77	0.82	0.88	0.87	0.70	0.79
03	SGD Classifier	0.93	0.92	1.00	1.00	1.00	0.79
04	K-Nearest Neighbors	0.30	0.26	0.31	0.00	0.00	0.79
05	Multinomial Naive Bayes	0.76	0.78	0.81	0.82	0.27	0.79

06	Random Forest	0.94	0.95	0.89	1.00	1.00	0.79

Table. 7 Recall

Sl.No	Classifiers	Culture	Devotion	Donative	Eulogistic	Memorial Stones	War
01	Linear SVC	0.88	0.94	1.00	1.00	1.00	0.97
02	Logistic Regression	0.82	0.85	0.80	0.83	0.54	0.89
03	SGD Classifier	0.92	0.94	1.00	1.00	1.00	0.99
04	K-Nearest Neighbors	0.44	0.27	0.23	0.00	0.00	0.52
05	Multinomial Naive Bayes	0.78	0.87	0.78	0.75	0.15	0.84
06	Random Forest	0.94	0.94	1.00	1.00	1.00	1.00

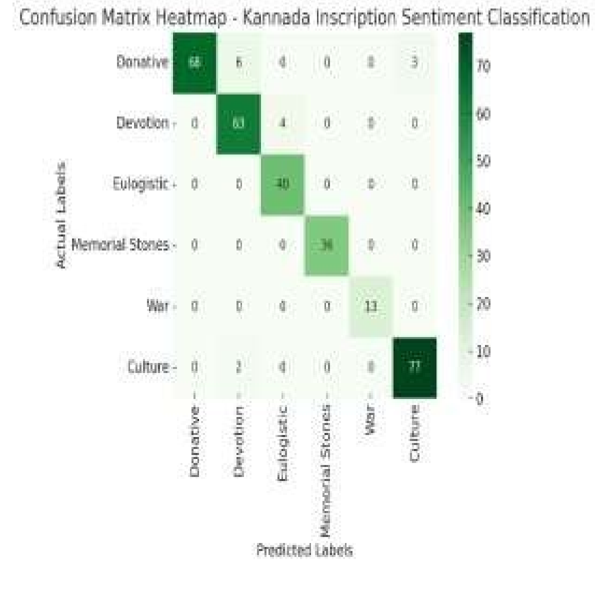

Fig 4. Confusion Matrix for the Linear SVC Classifier

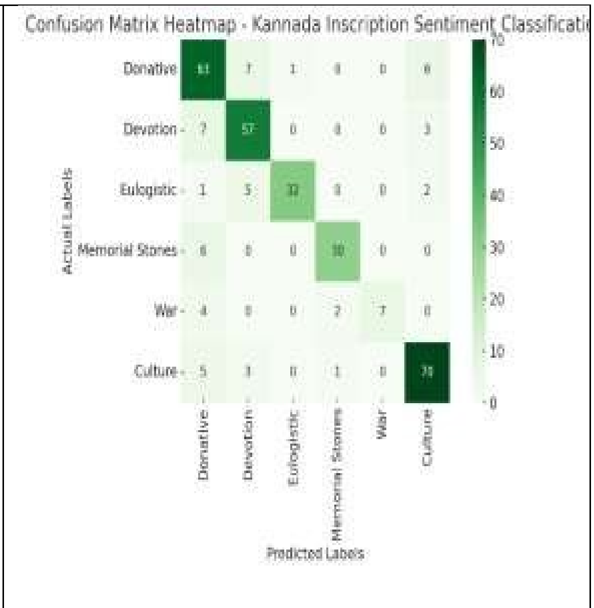

Fig 5. Confusion Matrix for the Logistic Regression Classifier

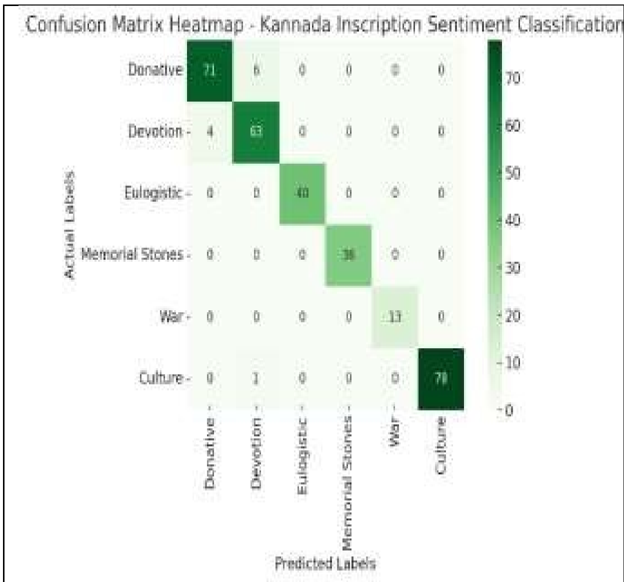

Fig 6. Confusion Matrix for the SGD Classifier

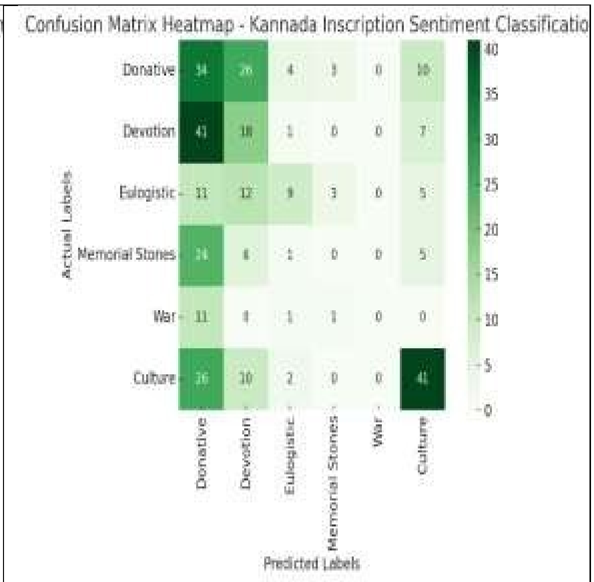

Fig 7. Confusion Matrix for the K-Nearest Neighbors Classifier

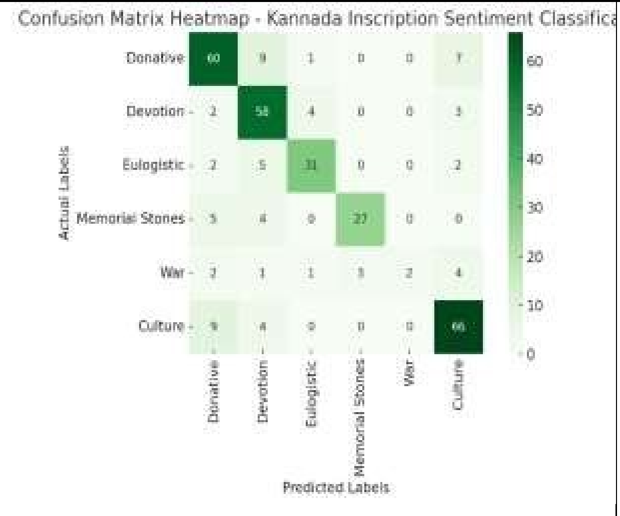

Fig 8. Confusion Matrix for the Multinomial Naive Bayes Classifier

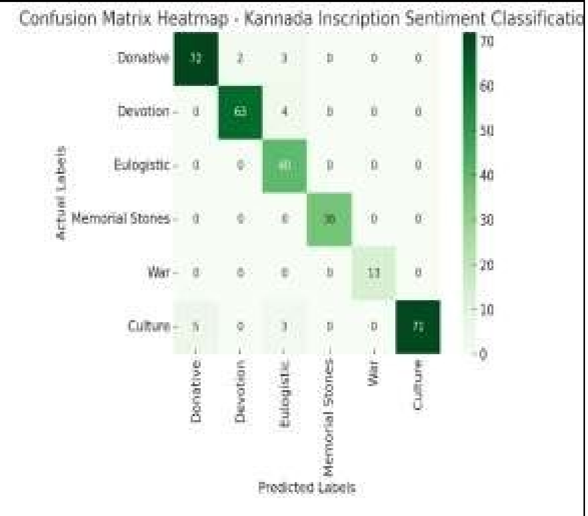

Fig 9. Confusion Matrix for the Random Forest Classifier

6. CONCLUSION

Psychological, sentimental, and emotional analyses together uncover how Kannada inscriptions functioned not just as records of events but as expressive, emotive, and persuasive instruments. They expose the human dimension of epigraphy the feelings, intentions, and psychological narratives woven into stone. Only a few studies have attempted to integrate computational models to extract psychological or emotional features from ancient texts. This gap in research highlights the need for interdisciplinary methodologies that merge NLP, computational linguistics, and historical analysis. This research demonstrates that Kannada inscriptions encapsulate not only historical facts but also profound emotional and psychological undercurrents. The psychological exploration of Kannada inscriptions through sentiment analysis represents a new frontier in digital humanities and cultural research. This study highlights the effectiveness of computational sentiment analysis in revealing the psychological and emotional depth of Kannada inscriptions. The results show that war-related expressions dominate the corpus, suggesting that language was used as a tool of political authority and emotional influence. The analysis shows that the SGD Classifier, Linear SVC, and Random Forest models performed best in identifying emotional tones within Kannada inscriptions. These models were effective in understanding complex expressions related to power, devotion, and culture found in ancient texts. In contrast, models like Logistic Regression and Naive Bayes could recognize general sentiment patterns but often missed the deeper emotional meanings within poetic or formal inscriptional language. The K-Nearest Neighbors model performed the weakest, as it struggled to interpret the rich and varied vocabulary typical of old Kannada inscriptions. Overall, the results suggest that advanced machine learning models are better suited to uncover the emotional and psychological layers present in historical Kannada writings.

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