International Journal of Computational Intelligence Research
ISSN 0973-1873 Volume 22, Number 1 (2026), pp.27-43

https://www.ripublication.com

Monitoring and Sorting of Terrorist and Radical Content in Social Network Messages using Regression Learning-Based Bayesian Regularized ANN

Mr. Nayan Joshi, Dr. Vivek Gupta
Medi-Caps University, Indore, India
Engr.nayanjoshi@gmail.com
Guptav06@gmail.com

Abstract

Social media platforms have become one of the most widely used communication mediums in the modern digital era. With the rapid advancement of technology and increasing digital dependency, these platforms have also been exploited for malicious activities, including the dissemination of extremist and radical content. The vast and diverse nature of user-generated data makes it challenging for security agencies and platform administrators to accurately distinguish between harmful and non-harmful content, especially due to the absence of clear boundaries.

In recent years, artificial intelligence techniques have shown significant potential in addressing such challenges through automated content classification and analysis. This paper proposes an intelligent framework based on dictionary learning integrated with a Bayesian Regularized Artificial Neural Network (BR-ANN) to detect and classify radical content on social media platforms. The proposed model is evaluated using key performance metrics such as iteration count, computational time, and classification accuracy.

Experimental results demonstrate that the proposed approach achieves a classification accuracy of 97%, outperforming existing methods that report an accuracy of 89%. The implementation of this system can assist social media platforms and security agencies in effectively monitoring, detecting, and mitigating the spread of extremist content, thereby contributing to a safer and more secure online environment.

Keywords: Social Network, Radical Content, Machine Learning, ANN, Bayesian Regularization

I. Introduction

With the widespread adoption of social media across all aspects of modern life, its misuse for spreading hatred and radical content has also significantly increased [1]. The rapid growth of digital communication platforms has enabled extremist groups to exploit these channels for propaganda and recruitment purposes. Despite global efforts by international coalitions and defense organizations, effectively combating such threats remains a major challenge due to the lack of transparency and clear timelines in counter-terrorism operations [2]–[4].

Extremist organizations, such as the Islamic State of Iraq and the Levant (ISIL), have leveraged social media and internet-based platforms to maximize their influence, particularly targeting technologically aware and younger populations [6]–[8]. These groups frequently disseminate professionally produced multimedia content, including videos, images, and narratives designed to promote their ideology and recruit members. Such content is distributed regularly, contributing to what is often referred to as "media-driven propaganda," which has become a significant component of modern extremist strategies.

Furthermore, these organizations utilize financial resources and digital tools to sustain and expand their online presence [9]–[14]. Instant messaging services and social networking platforms are commonly used to circulate propaganda messages and coordinate activities. One of the most effective countermeasures involves identifying and blocking such accounts; however, this requires analyzing and processing vast volumes of unstructured data [15]–[18].

The scale of data generated across different social media platforms, as illustrated in Table I, highlights the complexity of monitoring and filtering harmful content [19]. The absence of clear distinctions between radical and non-radical content further complicates the classification process. Consequently, manual analysis becomes inefficient and impractical.

This paper aims to address these challenges by exploring the impact of radical content on social media and proposing an advanced machine learning-based approach for its detection and classification. The study reviews existing methodologies and introduces an improved model that demonstrates superior performance compared to previous approaches. The findings contribute to enhancing automated content moderation systems and provide valuable insights for future research in this domain.

II. Objective

The primary objective of this work is to design and implement an automated classification system capable of detecting and categorizing radical content on social media platforms. The study focuses on developing an intelligent and efficient solution to address the challenges associated with large-scale content analysis.

The key objectives of this research are as follows:

- To develop a classification system based on advanced artificial intelligence techniques.
- To ensure accurate and effective identification of radical and non-radical content.
- To extract and analyze significant features that contribute to reliable content classification.
- To achieve a high level of classification accuracy and performance.
- To implement a robust and scalable methodology suitable for real-world applications.

III. Motivation

The rapid growth of social media platforms has resulted in an exponential increase in the volume of user-generated content. While these platforms facilitate communication and information sharing, they also present significant challenges in distinguishing between legitimate and potentially harmful or malicious content. Identifying and controlling the spread of radical content has become increasingly difficult due to the scale and complexity of the data involved.

Conventional methods are often inadequate for handling such large and diverse datasets, highlighting the need for more advanced and robust solutions. The vast amount of digital information generated daily emphasizes the importance of efficient classification techniques to detect and prevent the dissemination of harmful content.

To address these challenges, it is essential to leverage advanced technologies such as artificial intelligence and machine learning. These approaches enable automated analysis, improving both the speed and accuracy of content classification. Effective filtering and detection of radical content are crucial for ensuring responsible use of social media platforms and for mitigating the spread of misinformation and extremist material.

IV. Literature Review

This section reviews existing approaches for identifying and classifying terrorist and radical content on web-based and social media platforms, along with their key contributions and limitations.

In [1], Kapitonov *et al.* focused on analyzing malicious messages shared by terrorist communities across social media and instant messaging platforms. The study proposed a machine learning-based approach to automate the classification of radical content. However, the model primarily relied on conventional statistical techniques, which limited its effectiveness in handling complex datasets.

In [2], Lopez *et al.* introduced a framework for automatically monitoring radical activities on Twitter. Their approach emphasized identifying users prone to spreading extremist content and analyzing their interaction patterns. Although validated through a case study, the model faced challenges in clearly distinguishing between overlapping content categories, thereby affecting classification precision.

Bobashev *et al.* in [3] investigated radical communication patterns associated with the 1995 Paris metro attack using natural language processing (NLP) and dynamic visualization techniques. While the study provided valuable insights into group formation and behavior, its reliance on early-stage NLP techniques limited its overall performance and accuracy.

In [4], Sun *et al.* proposed a strategy for predicting terrorist group activities using advanced analytics. Their findings highlighted the importance of feature extraction in improving classification performance. However, the study emphasized that conventional approaches are insufficient for handling large-scale and complex datasets, indicating the need for more sophisticated models.

Tundis *et al.* in [5] explored text analysis techniques for identifying radical content on social media. Their approach incorporated linguistic features but faced challenges in

accurately classifying content based on single-word analysis. The study suggested that multi-token or contextual analysis could significantly improve classification accuracy.
In [6], Al-Zewairi *et al.* applied multiple supervised machine learning algorithms to analyze the behavioral traits of extremist individuals. Although combining multiple algorithms improved performance, insufficient data pre-processing negatively impacted classification effectiveness.
Johnston *et al.* in [7] investigated extremist propaganda on the dark web using deep learning and neural network models. While the approach demonstrated promising results, the use of a single neural network limited scalability and performance when handling large datasets. The authors recommended the use of hybrid or ensemble models for improved accuracy.
Ishitaki *et al.* in [8] studied the use of the Tor network for spreading radical content. Their work highlighted the role of user anonymity in accelerating the dissemination of malicious information. Although deep learning techniques were applied, the study suggested that incorporating probabilistic approaches could further enhance classification accuracy.
In [9], Lourentzou *et al.* explored deep neural networks for location-based prediction of radical content. Their approach utilized geographic information for classification; however, the lack of clear boundaries between radical and non-radical data posed a significant challenge. Additionally, the need for more diverse datasets was identified to improve model performance.
Lara-Cabrera *et al.* in [10] analyzed behavioral patterns of extremist groups on social media using deep learning techniques. Despite achieving satisfactory results, the study faced limitations due to inadequate data pre-processing and the inability of a single neural network to effectively handle large-scale datasets.
Recent contributions by S. Jain *et al.* further demonstrate the effectiveness of machine learning across multiple domains. In [33], an algorithmic trading strategy based on machine learning was proposed to optimize financial decision-making through predictive modeling. In [34], a hybrid approach integrating machine learning and statistical methods was developed to improve diagnostic accuracy in clinical applications, significantly reducing false predictions. In [35], an optimized machine learning pipeline was introduced for real-time object detection in automotive and surveillance systems, focusing on enhancing accuracy while reducing computational complexity.

V.SIGNIFICANCEOFRADICALCONTENTON SOCIAL MEDIA

The volume of data generated on social networking platforms is extremely large, making manual analysis impractical and inefficient [25]–[27]. To highlight the scale and complexity of this data, Table I presents a frequency analysis of content generated across major social media platforms in table 1.

Table I: Content Generated on Social Media Platforms

Social Media	Messages per Second	Messages per Day	Messages per Month	Active Users
WhatsApp	636 thousand	55 billion	1.6 trillion	2.78 billion
Telegram	175 thousand	15 billion	450 billion	700 million
Facebook	2.5 thousand	216 billion	6.5 billion	3 billion
Twitter	5.8 thousand	500 billion	15 billion	353.9 million
Instagram	1 thousand	95 billion	2.8 billion	2.5 billion

The increasing popularity of social media platforms has brought both advantages and challenges. A large number of users actively engage with these platforms on a daily basis, resulting in the continuous generation of massive volumes of data. Due to prolonged exposure, users—particularly younger individuals—are more susceptible to the influence of online content, which is often exploited by extremist groups to disseminate radical ideologies.

To effectively analyze such vast and complex datasets, the use of artificial intelligence and machine learning techniques becomes essential. Artificial Neural Networks (ANNs) can be employed to identify hidden patterns and classify content efficiently. Techniques such as Named Entity Recognition (NER) are widely used to extract structured information from unstructured text, particularly in short social media messages. Additionally, methods such as clustering, logistic regression, and Dynamic Query Expansion (DQE) are useful in predicting potential terrorist activities and social unrest.

Several machine learning algorithms have been applied for real-time detection of radical content, including K-Nearest Neighbors (KNN), Naïve Bayes, Support Vector Machines (SVM), and decision trees. However, due to the absence of clearly defined boundaries between radical and non-radical content, probabilistic classifiers are often preferred for improved accuracy.

The task of analyzing extremist content presents several challenges. Social media messages are typically short, informal, and often include slang, abbreviations, or coded language, making semantic analysis difficult. Furthermore, multilingual communication and mixed-language content add to the complexity of classification [28]. Traditional keyword-based approaches are insufficient, as they fail to distinguish between harmful content and legitimate sources such as news or academic discussions. The sheer volume of data also makes manual filtering ineffective, emphasizing the need for automated classification systems [29].

Another challenge lies in identifying the source or affiliation of radical content, as different extremist groups often use similar language and narratives. Additionally, the strategic use of hashtags by such groups enables rapid and widespread dissemination of content. For example, coordinated campaigns using specific hashtags can significantly amplify visibility and influence.

To address these challenges, the proposed approach involves multiple processing stages. Initially, text preprocessing is performed to remove noise, including hyperlinks, symbols, and stop words. This is followed by spelling correction using techniques such as Levenshtein distance [30]. Subsequently, a Naïve Bayes classifier is applied to categorize messages into radical and non-radical classes. However, since some messages may criticize or oppose extremist views, additional sentiment or tone analysis is required to accurately distinguish between supportive and opposing content.

VI. METHODSANDMATERIALS

Proposed Methodology

The need to analyze large-scale and complex datasets necessitates the use of machine learning–based approaches for effective radical content classification. The proposed method integrates **regression learning** with **Bayesian classification** to enhance prediction accuracy and robustness. Regression learning is utilized to determine the optimal mapping between input features and labeled outputs, while Bayesian classification applies probabilistic reasoning based on conditional probability.

This hybrid approach also provides insight into the **weight update mechanism** of the neural network, which governs how the model learns from data and improves over iterations.

System Design Using Regression Learning-Based Bayesian Regularized ANN

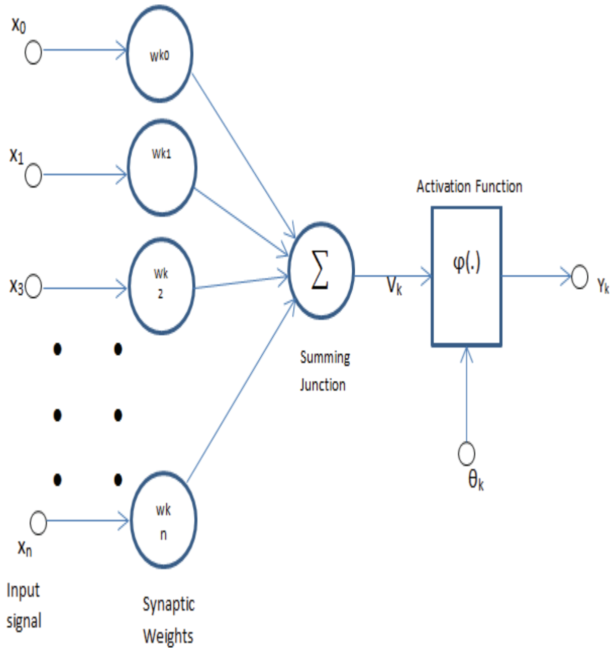
Artificial Neural Networks (ANNs) are highly effective in extracting meaningful patterns from complex and ambiguous datasets, where traditional computational methods fail. Their capability to generalize knowledge makes them suitable for detecting radical content in unstructured social media data.

The major advantages of ANN include:

- **Adaptive Learning:** Ability to learn from training data and improve performance over time.
- **Self-Organization:** Capability to automatically structure and represent learned information.
- **Real-Time Processing:** Supports parallel computation, enabling efficient real-time analysis.

1. Regression Learning Model

Regression learning is a supervised learning technique used to establish relationships between dependent and independent variables [31]. In this work, regression is used to model the relationship between input features and predicted outputs.



where:

- x represents the input feature vector,
- y represents the predicted output,
- θ_1 and θ_2 are model parameters.

The objective is to determine optimal parameter values that minimize the prediction error. This is achieved by minimizing the cost function J, defined as the Mean Squared Error (MSE):

$$J = \frac{1}{n}\sum_{i=1}^{n}(pred_i - y_i)^2$$

where:

- n is the number of samples,
- predi is the predicted value,
- yi is the actual value.

2. Gradient Descent in Regression Learning

Gradient Descent is employed to iteratively update the model parameters θ_1 and θ_2 in order to minimize the cost function. The process begins with randomly initialized values and updates them in the direction of the negative gradient until convergence is achieved.

In an ANN, each neuron receives multiple inputs Xi, each associated with a weight Wi . The neuron computes a weighted sum followed by the addition of a bias θ, expressed as:

$$\sum_{i=1}^{n} X_i W_i + \theta$$

The computed value is then passed through an activation function to produce the final output. The learning capability of the ANN depends on continuous adjustment of weights based on prediction error.

3. Bayesian Regularization

Bayesian Regularization (BR) enhances the generalization capability of neural networks by incorporating probabilistic principles based on Bayes' theorem. It improves upon traditional weight update methods such as the Levenberg–Marquardt (LM) algorithm [32].

The weight update rule in Bayesian Regularization is given by:

$$W_{k+1} = W_k - (J_k^T J_k + \mu I)^{-1} J_k^T e_k$$

where:

- Wk and Wk+1 are weights at current and next iterations,
- Jk is the Jacobian matrix,
- JkT is its transpose,
- μ is the learning parameter,
- III is the identity matrix,
  ek is the error vector.

The weights are dynamically updated as a function of iteration and error:

$$w(i) = f(i, e)$$

This iterative adjustment ensures that the model minimizes overfitting while maintaining high prediction accuracy.

4. Bayesian Classification Perspective

The Bayesian classifier determines the probability of a data instance belonging to a particular class based on prior and conditional probabilities. This process can be interpreted using concepts from set theory, where overlapping regions represent uncertainty between classes.

Such probabilistic modeling is particularly useful in radical content classification, where class boundaries are not well-defined and content may share similarities across categories.

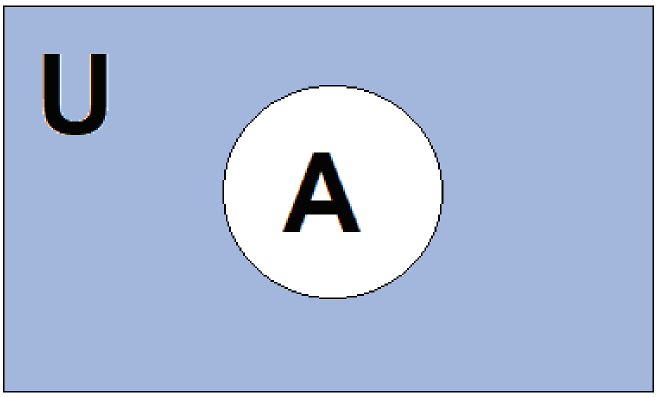


Fig.2 Universal Set Containing a Subset 'A'

Let's assume that the Bayesian Regularization algorithm must classify the set A among various subsets in the superset U, where A is currently the only set that exists.

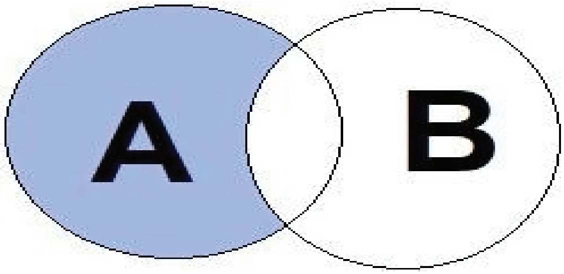


Fig.3 Probability of Exclusive Occurrence of 'A'

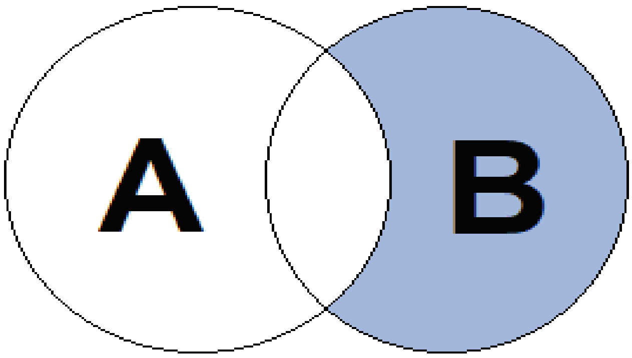


Fig.4 Probability of Exclusive Occurrence of 'B'

Figures 3 and 4 depict the probability of exclusive occurrence of events A and B respectively.

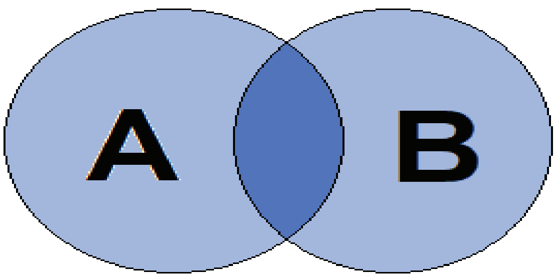


Fig.5 Probability of Union of A and B

Assume that the **Bayesian Regularization (BR) algorithm** is required to classify a dataset belonging to subset **A** within a universal set **U**, which may contain several subsets representing different classes.
For the experimental setup, **70% of the dataset is used for training**, while the remaining **30% is used for testing**.
In this classification framework, sentiment or category identification can be interpreted as overlapping probability events. The class associated with the **highest conditional probability** is selected as the final classification outcome.
The conditional probabilities for different subsets within the universal set can be represented as:

$$P(A),\ P(B),\ \dots,\ P(N) \qquad (8)$$

The **Bayesian Regularization algorithm** determines the maximum probability among these classes:

$$P_{\max} = \max\{P(A), P(B), \dots, P(N)\} \qquad (9)$$

The classification decision is determined by selecting the class corresponding to the **maximum probability value**. If a dataset instance belongs to class X, then:

$$P_{\max} = X \qquad (10)$$

and

$$P(X) = P_{\max} \qquad (11)$$

where:

- Xrepresents the class with the highest probability value.
- $n$represents the total number of classes in the classification problem.

The cumulative conditional probability across all possible classes can be expressed as:

$$\prod_{i=1}^{n} U_i$$

where:

- $U_i$represents the conditional probability of each class,
- $n$denotes the total number of classification categories.

5. Evaluation Parameter

Since prediction errors may have either positive or negative signs, directly summing them may lead to cancellation and an incorrect evaluation of system performance. Therefore, magnitude-based metrics are preferred for evaluation.
In this work, **Mean Squared Error (MSE)** and **Mean Absolute Percentage Error (MAPE)** are used as performance evaluation metrics.
The **Mean Squared Error (MSE)** is mathematically defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(X_i - \hat{X}_i)^2 \qquad (12)$$

where:

- $X_i$represents the predicted value,
- $\hat{X}_i$represents the actual value,
- $n$represents the total number of samples.

A lower MSE value indicates better prediction accuracy and improved system performance.

Fig. 5. Probability of Union of Events A and B
Figure 5 illustrates the probability of the **union of events A and B**, representing the combined probability space where either event may occur.

5.1. Dataset
Algorithms for the classification of text documents with regard to radical content were tested using data collected by researchers from the Artificial Intelligence Lab at the University of Arizona. These data represent information collected from various websites, forums, chats, blogs, social networking, etc. for designated terrorist organizations.

In the dataset, there are a lot of discussion branches on different thematic focuses. Information with potentially extremist content is not present in all branches. There are a lot of messages devoted to talking about religious subjects, like how to behave in an Islamic society, how men and women are treated there, etc. Aside from that, there are regular subjects like talking about cars, sports, and cooking. A significant portion of the message is devoted to discussing current political affairs that are somehow related to Russia, the Caucasus, and the Middle East, such as the wars in Afghanistan and Libya, the events in Georgia and Poland, and the accident at the Japanese nuclear power plant.

6.RESULT & DISCUSSION

6.1. Data Normalization

The process of bringing a text into a single format that is practical for further processing is known as canonization (normalization). Prepositions, particles, conjunctions, and other non-informative speech parts must be left out of documents when working with a lot of information.
A sample screenshot of the text data from various social media applications that will be analysed to look for radical content is shown in the figure.

Fig.2 Designed Neural Network and its training parameters

The neural network that was created has the following characteristics:
- To reduce the algorithm's complexity, only two hidden layers have been used.
- The mean square error serves as a performance evaluation criterion.
- Bayesian Regularization is the training algorithm.

6.2.

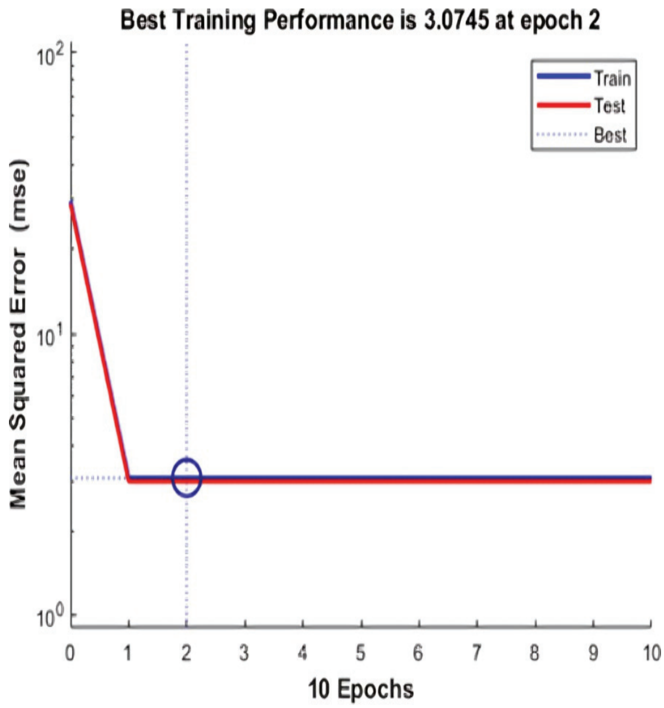


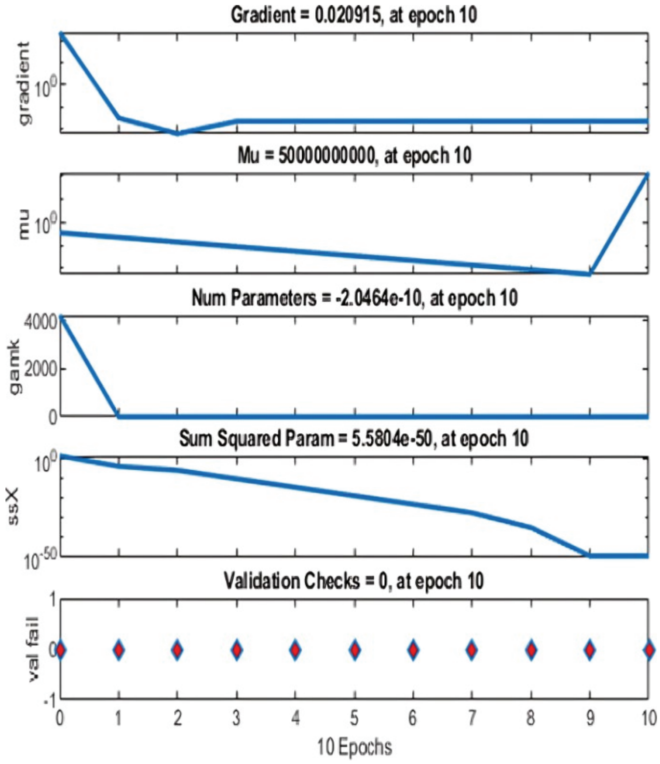
Fig.3 Training and epoch performance of the proposed system

The above figure displays the variation in mean squared error as a function of epochs. The MSE appears to stabilize at a value of 3.0745, as can be seen.

Figure 4 demonstrated that the proposed work achieves a much higher accuracy of 97%.

illustrates the variation in training states for the step size (mu), gradient, number of effective parameters, and sum squared parameters. Also demonstrated is the validation. According to mathematics, the gradient (g) and step size (μ) mathematically defined as: ∂e

REFERENCES



6.2 Performance Analysis

The experimental results demonstrate that the proposed model achieves a significantly improved classification accuracy of **97%**.

In the proposed Artificial Neural Network (ANN), the gradient of the error with respect to the weight is calculated to guide the learning process. The gradient is defined as:

$$g = \frac{\partial e}{\partial w} \qquad (13)$$

where:

- $e$represents the error,
- $w$represents the weight associated with the neural network.

The update parameter used in the training process is defined as:

$$\mu = W_k(1 - W_k) \qquad (14)$$

where:

- $k$represents the current iteration,
- $k + 1$represents the subsequent iteration.

The results clearly indicate that the proposed approach achieves an accuracy of **97%**, corresponding to an error rate of approximately **3%**. This performance is significantly better than previously reported methods.

The accuracy percentage is calculated using the following expression:

$$Accuracy(\%) = [100 - Error]\%$$

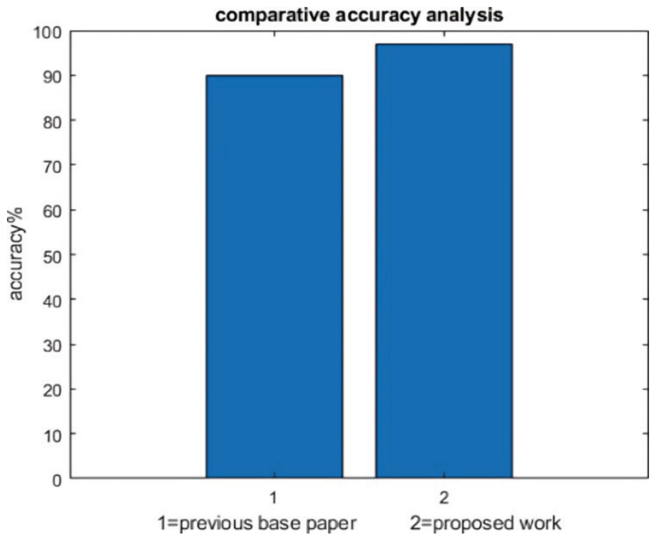


Fig.5 Comparative Accuracy Analysis w.r.t. previous work [1]

It is evident that compared to the previous work's accuracy of 89 percent, the proposed work achieves a much higher accuracy of 97 percent. This is explained by the fact that the regression learning-based BR trained ANN design has a steeper error descent curve than either the naive Bayes classifier or the traditional Bayesian Regularization algorithm.

VII. Conclusion

From the preceding discussion, it is evident that the rapid growth of social media as a primary mode of communication among individuals and communities has significantly increased the risk of its misuse for malicious activities. One of the major concerns is the widespread dissemination of radical content, facilitated by the ease of sharing information across large networks of users.

Identifying such harmful content within massive volumes of unstructured data remains a challenging task for social media platforms and security agencies. As the dataset size increases, the classification problem becomes more complex due to the absence of clear boundaries between radical and non-radical content.

To address this issue, a **Bayesian Regularized Artificial Neural Network (ANN)** based on regression learning has been proposed. The integration of regression learning with probabilistic Bayesian techniques enhances the model's ability to generalize and accurately classify ambiguous content.

Experimental results demonstrate that the proposed approach outperforms existing methods, achieving higher classification accuracy compared to the previously reported 89%. This improvement highlights the effectiveness of the hybrid model in detecting radical content on social media platforms.

References

[5] A. Tundis, G. Bhatia, A. Jain, and M. Mühlhäuser, “Supporting the identification and assessment of suspicious users on Twitter social media,” in *Proc. IEEE*, 2018.
[6] M. Al-Zewairi and G. Naymat, “Spotting the Islamist radical within: Religious extremists profiling in the United States,” *Elsevier*, 2017.
[7] A. H. Johnston and G. M. Weiss, “Identifying Sunni extremist propaganda with deep learning,” in *Proc. IEEE*, 2017.
[8] T. Ishitaki, R. Obukata, T. Oda, and L. Barolli, “Application of deep recurrent neural networks for prediction of user behavior in Tor networks,” in *Proc. IEEE*, 2017.
[9] I. Lourentzou, A. Morales, and C. X. Zhai, “Text-based geolocation prediction of social media users with neural networks,” in *Proc. IEEE*, 2017.
[10] R. Lara-Cabrera, A. Gonzalez-Pardo, M. Barhamgi, and D. Camacho, “Extracting radicalisation behavioural patterns from social network data,” in *Proc. IEEE*, 2017.
[11] L. Ball, *Automating Social Network Analysis: A Power Tool for Counter-Terrorism*. Springer, 2016.
[12] T. Ishitaki, T. Oda, and L. Barolli, “A neural network-based user identification for Tor networks: Data analysis using Friedman test,” in *Proc. IEEE*, 2016.
[13] T. Oda *et al.*, “A neural network-based user identification for Tor networks: Comparative analysis of different activation functions using Friedman test,” in *Proc. IEEE*, 2016.
[14] T. Sabbah *et al.*, “Hybridized term-weighting method for dark web classification,” *Elsevier*, 2016.
[15] R. Scrivens and R. Frank, “Sentiment-based classification of radical text on the web,” in *Proc. IEEE*, 2016.
[16] T. Sabbah and A. Selamat, “Hybridized feature set for accurate Arabic dark web pages classification,” *Springer*, 2015.
[17] T. Ishitaki, T. Oda, and L. Barolli, “Application of neural networks and Friedman test for user identification in Tor networks,” in *Proc. IEEE*, 2015.
[18] R. Frank, M. Bouchard, G. Davies, and J. Mei, “Spreading the message digitally: A look into extremist organizations’ use of the Internet,” *Springer*, 2015.
[19] T. Sabbah and A. Selamat, “Hybridized feature set for accurate content Arabic dark web pages classification,” *ResearchGate*, 2015.
[20] B. Agarwal *et al.*, “Concept-level sentiment analysis with dependency-based semantic parsing: A novel approach,” *Springer*, 2015.
[21] B. Akhgar, F. Tabatabayi, and P. S. Bayerl, “Investigating radicalized individual profiles through fuzzy cognitive maps,” *Elsevier*, 2014.
[22] A. Yucel and Koltuksuz, “An annotated bibliographical survey on cyber intelligence for cyber intelligence officers,” *JSTOR*, 2014.
[23] A. Modupe, O. O. Olugbara, and S. O. Ojo, “Filtering of mobile short messaging service communication using latent Dirichlet allocation with social network analysis,” *Springer*, 2014.
[24] W. Cherif, A. Madani, and M. Kissi, “Integrating effective rules to improve Arabic text stemming,” in *Proc. IEEE*, 2014.

[25] J. Drouin, "Close- and distant-reading modernism: Network analysis, text mining, and teaching the Little Review," *JSTOR*, 2014.
[26] P. Wadhwa and M. P. S. Bhatia, "Tracking online radicalization using investigative data mining," in *Proc. IEEE*, 2013.
[27] N. Kim *et al.*, "Multiscale modeling of radical and counter-radical Islamic organizations," *ResearchGate*, 2013.
[28] N. Kim, S. Gokalp, H. Davulcu, and M. Woodward, "LookingGlass: A visual intelligence platform for tracking online social movements," in *Proc. IEEE*, 2013.
[29] N. G. Khan and V. B. Bhagat, "Effective data mining approach for crime-terror pattern detection using clustering algorithm technique," *Semantic Scholar*, 2013.
[30] M. Munezero, M. Mozgovoy, and T. Kakkonen, "Antisocial behavior corpus for harmful language detection," in *Proc. IEEE*, 2013.
[31] M. Hagan, H. Demuth, and M. Beale, *Neural Network Design*, 2nd ed.
[32] "Mastering Machine Learning," [Online]. Available: http://coursera.org/
[33] S. Jain *et al.*, "An algorithmic trading strategy using machine learning," in *Data Mining and Information Security: Proc.*, 2025.
[34] S. Jain *et al.*, "Integrating machine learning and statistical approaches to improve diagnostic accuracy in clinical practice," *International Journal of Environmental Sciences*, 2025.
[35] S. Jain *et al.*, "Optimized machine learning pipeline for object detection in automotive and surveillance systems," in *Proc. SciTePress iCRDICCT*, 2025.