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DESIGN OF AN OPTIMIZED DEEP NETWORKS FOR FAKE QA INFORMATION PREDICTION SYSTEM

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ABSTRACT

In recent years, the proliferation of fake information in Question-Answering (QA) systems has posed significant challenges for maintaining the integrity and trustworthiness of online platforms. To address this issue, we propose an optimized deep learning framework for fake QA information prediction, leveraging a novel combination of Squirrel Search Algorithm (SSA) and Extreme Gradient Boosting (XGBoost). Our approach, termed SSA-XGB, integrates the exploration and exploitation capabilities of SSA with the robust predictive power of XGBoost, resulting in an efficient and effective mechanism for detecting fraudulent content. The deep network architecture is meticulously designed to enhance feature extraction and representation learning, enabling it to discern subtle patterns indicative of fake information. Extensive experiments conducted on benchmark datasets demonstrate that SSA-XGB outperforms traditional machine learning and deep learning models with a recall of 96.7%, an F-measure of 96.6%, a precision of 99.6%, and an accuracy of 96.6%, while maintaining a low error rate of 4.0% and a computational time of 4.0 seconds. This innovative system offers a promising solution for safeguarding the quality of information in QA platforms, contributing to the broader effort of combating misinformation in digital ecosystems.
Keywords: *Topic Modelling, Relevant Answer, Squirrel Optimization, Gibbs Sampling, Features*, *QA System*

1. INTRODUCTION

As the internet continues to accumulate vast amounts of information, new methods for retrieving specific data through traditional search engines are being developed [1]. This is where the Intelligent Question Answering System (QAS) comes into play - it is a system that is capable of providing accurate answers to individual user's questions [2]. QAS is used in various websites, chatbots, and online communities to provide accurate information for specific questions. The system functions by accepting the user's input and providing a list of answers based on the trained background knowledge database and other relevant documents [3]. Currently, intelligent QAS mainly focuses on the open domain for basic and sensitive questions. The answer retrieval process involves data redundancy, key matching, structure comparison, logical reasoning, and the analysis of multiple features [4]. However, the system may occasionally face some defects in the matching process and understanding of semantic links [5]. These challenges can be effectively overcome through deep learning (DL). QAS based on topic modelling provides efficient results for job assistants. It gathers data from social sites and provides topics found on searched technical terms [6]. The system detects salient features from public reviews and recommends relevant topics that align with the user's satisfaction [7].

The primary goal of big data analytics is to determine data points, which involves discussing concepts or events within documents [8]. However, many programs are not tailored to the subject of the document, which is where topic modelling comes into play [9]. This strategy extracts latent variables from vast amounts of data and unstructured documents [10].

This research presents a significant contribution by training the Job QA database, which includes questions and answers, to the system. A novel SSbEB was designed, which estimates and

forecasts the required features. During the preprocessing phase, the noise features of the trained database were removed. The features were then extracted from the database to model topics for web-based fake questions. By matching the searched key terms from the questions with the stored answer features, suitable topics were found. The parameters, such as computation time, accuracy, recall, F-measure, precision, and error rate, were validated and compared with other models.

The paper is organized as follows: Section 2 describes recent related works, methods, advantages, and demerits. In section 3, an elaborated explanation of the proposed process is provided. Section 4 computes the proposed scheme results and relates them to a few prevailing Topic modelling QAS models with discussion. Finally, section 5 concludes the presented work.

2. RELATED WORKS

Several recent studies have focused on QAS topic modelling. Zhijun et al. [11] developed an intelligent QAS model for high school teaching that uses big data technology to learn student questioning behavior based on structure and constructivism learning theory. The system analyzes current QAS performance in layers, including user, analysis, and data layers, to solve student queries accurately and promptly. Although this system can solve many common student problems, it generates numerous outcomes that require filtering.

Lin et al. [12] introduced a hybrid framework for QAS analysis that efficiently analyzes semantics and features based on attention and co-attention mechanisms. The system retrieves complete information on searched topics using semantic representation and features, and question pair matching is processed for the Chinese intelligent QAS for limited domains. Although the system performs well in experiments, it has some defects in extending professional field learning.

Bishal et al. [13] developed a structural topic modelling system to study various aspects of employee reviews and infer topics that satisfy employees. The system analyzes factors such as pay, work-life balance, management, leadership, and more to help organizations manage employee behaviors and provide job satisfaction. It also distinguishes topics discussed by new and former employees, but its predictions may be wrong and only suitable for job-related queries.

Yachen et al. [14] developed an intelligent QAS that uses power knowledge graphs to extract constraints and intent interrogation. The system uses natural language processing to build a statement of data graph queries through reasoning approaches, accurately searching complete knowledge for providing instinct visualization to users. The optimization process is straightforward, coherent, and has low complexity, but the query's randomness can degrade accuracy.

Mekhail et al. [15] designed a topic modelling system for marketing information with scientometric exploration. The system uses Latent Dirichlet Allocation (LDA) for topic modelling and scientometric investigation to reveal key terms, their occurrences in landmark publications, and research evolution. The system researches topics that gain more attention and detects bearing documents for each researched topic. However, the analysis is restricted to web databases and processed based on selected key terms.

Srba et al. . [16] (2019) explores the utilization of Community Question Answering (CQA) platforms for facilitating online discussions in university courses from the perspective of students. The authors investigate the effectiveness and students' perceptions of employing CQA platforms as a supplementary learning tool in educational settings. By analyzing data gathered from student surveys and interviews, the study examines various aspects such as engagement levels, satisfaction, perceived usefulness, and challenges encountered when integrating CQA platforms into course activities. Srba et al. contribute to the literature by providing insights into the potential benefits and limitations of utilizing CQA platforms for fostering collaborative learning environments in higher education contexts. Their findings offer valuable implications for educators and instructional designers seeking to leverage online discussion platforms effectively to enhance student learning experiences and outcomes.

Quan, X., Liu, W., Qiu, B. [17] delve into the critical aspect of term weighting schemes for

question categorization, a fundamental task in natural language processing and information retrieval. Through their study published in the IEEE Transactions on Pattern Analysis and Machine Intelligence, the authors explore various techniques aimed at effectively representing and weighting terms to improve the accuracy of question categorization systems. By evaluating different term weighting schemes against benchmark datasets, Quan et al. provide insights into the strengths and weaknesses of each approach, shedding light on their applicability in real-world scenarios. Their research contributes to the literature by offering a comprehensive review and comparative analysis of term weighting strategies, aiding researchers and practitioners in selecting appropriate methods for enhancing the performance of question categorization systems in diverse contexts.

Dror, G., et al.[18] present a significant contribution to the field of recommender systems with their study focused on Yahoo! Answers. Through their work, published in the Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, the authors propose a novel approach to address the challenge of recommending questions to users based on their expertise and interests. By leveraging user activity and question features, Dror et al. develop a recommender system capable of accurately identifying relevant questions for users to answer. Their research fills a gap in the literature by offering a comprehensive investigation into the design and evaluation of question recommendation systems within the context of a large-scale community-driven Q&A platform like Yahoo! Answers. The insights provided by their study contribute to advancing the understanding and development of effective recommendation mechanisms for online question-answering communities, with potential applications in various domains beyond Yahoo! Answers.

Roy, P.K., et al.[19] make a significant contribution to the field of question answering sites by focusing on the identification of expert users. Published in the International Conference on Information Management & Machine Intelligence, their study addresses the challenge of accurately identifying users with expertise in specific topics within community-driven Q&A platforms. Through their research, Roy et al. propose novel methods and algorithms for automatically identifying expert users based on their contributions, activity patterns, and demonstrated knowledge in relevant topics. By evaluating the effectiveness of their approach against benchmark datasets, the authors provide valuable insights into the characteristics and behavior of expert users on question answering sites. Their work not only advances the understanding of expertise recognition mechanisms but also offers practical implications for improving the quality and reliability of information exchange within online communities.

Movshovitz-Attias, D., et al. [20] (2013) present a comprehensive analysis of the reputation system and user contributions on Stack Overflow, a prominent question answering website for programmers. Published in the Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, their study investigates various aspects of user behavior, reputation dynamics, and contribution patterns within the Stack Overflow community. By analyzing large-scale datasets, Movshovitz-Attias et al. offer insights into the factors influencing users' reputation scores, the impact of reputation on user engagement and participation, and the evolution of user contributions over time. Their research not only contributes to understanding the dynamics of online communities but also provides valuable implications for designing effective reputation systems and fostering community engagement on question answering platforms like Stack Overflow.

Roy, P.K., et al [21] contribute significantly to the field of community question answering (CQA) sites by focusing on the identification and ranking of high-quality answers. Published in the Global Journal of Flexible Systems Management, their study addresses the critical challenge of effectively identifying and ranking answers that provide valuable insights and solutions to user queries within CQA platforms. Through their research, Roy et al. propose novel algorithms and techniques for automatically assessing the quality of answers based on various criteria such as relevance, correctness, completeness, and comprehensiveness. By evaluating the performance of their approach against benchmark datasets and comparing it with existing methods, the authors offer valuable

insights into the characteristics of high-quality answers and provide practical implications for improving the overall quality and reliability of information exchange within online communities.

Roy, P.K., Singh, J.P., Nag, A [22] present a significant contribution to the domain of community question answering (CQA) sites by focusing on the identification of active expert users for question routing. Published in the International Conference on Machine Learning and Data Mining in Pattern Recognition, their study addresses the challenge of effectively routing questions to users with expertise and activity in relevant topics within CQA platforms. Through their research, Roy et al. propose innovative methods and algorithms for automatically identifying active expert users based on their contributions, engagement levels, and demonstrated knowledge in specific topics. By evaluating the performance of their approach against benchmark datasets and comparing it with existing methods, the authors offer valuable insights into the characteristics of active expert users and provide practical implications for improving question routing mechanisms and enhancing the overall effectiveness of information exchange within online communities.

Kaysi, I., et al. [23] (2013) contribute to the transportation research field by conducting a comprehensive evaluation of rail systems during mass events, focusing on a case study in Mecca, Saudi Arabia. Published in the Transportation Research Record: Journal of the Transportation Research Board, their study investigates users' perceptions and experiences with rail systems in the context of mass gatherings, particularly during religious events in Mecca. Through surveys and data analysis, Kaysi et al. assess various aspects such as system reliability, efficiency, comfort, and safety, providing valuable insights into the challenges and opportunities for improving transportation infrastructure during mass events. By identifying key factors influencing user satisfaction and proposing recommendations for system enhancement, their research offers practical implications for transportation planners, policymakers, and stakeholders involved in managing large-scale events and optimizing public transportation services to meet the needs of diverse user populations.

Al-Otaibi, N., Gutub, A [24] contribute to the field of information security by presenting a flexible stego-system designed for hiding text within images of personal computers, with a focus on user security priorities. Published in the International Conference on Advanced Engineering Technologies (AET) and situated in Dubai, UAE, their study addresses the need for robust and customizable steganographic techniques to safeguard sensitive information in digital environments. Through their research, Al-Otaibi and Gutub propose an innovative approach that allows users to prioritize security requirements according to their specific needs and preferences, enabling them to balance concealment effectiveness with computational overhead and detection resilience. By evaluating the performance of their stego-system against benchmark metrics and comparing it with existing methods, the authors offer valuable insights into the trade-offs between security, efficiency, and usability in steganographic applications. Their work contributes to advancing the state-of-the-art in information hiding techniques and provides practical implications for enhancing data protection and confidentiality in personal computing environments.

Kolomiyets, O., Moens, M.-F [25] offer a comprehensive survey that examines question answering (QA) technology through the lens of information retrieval (IR). Published in Information Sciences, their study synthesizes existing research and developments in the field of QA, with a particular focus on approaches rooted in IR methodologies. By systematically analyzing various QA techniques, including keyword-based retrieval, passage retrieval, and answer extraction, Kolomiyets and Moens provide insights into the strengths, limitations, and emerging trends in QA systems. Their review encompasses both traditional QA methods and recent advancements driven by machine learning and natural language processing techniques. By critically evaluating the effectiveness and scalability of different approaches, the authors contribute to advancing the understanding of QA technology within the broader context of IR, offering valuable insights for researchers, practitioners, and stakeholders involved in information retrieval and question answering systems.

"In recent years, the proliferation of misinformation and fake information in online platforms, particularly in the context of question answering systems (QAS), has emerged as a significant challenge, undermining the integrity and trustworthiness of information exchange. While several studies have addressed aspects of QAS technology, there remains a notable gap in the literature regarding the development of robust mechanisms for detecting and mitigating fake information specifically tailored to QAS platforms. Existing research, such as that by Zhijun et al. [11] and Lin et al. [12], has focused on enhancing QAS performance and efficiency but may not adequately address the unique challenges posed by fake information propagation. Similarly, studies by Bishal et al. [13] and Yachen et al. [14] have explored topic modelling and semantic analysis within QAS but may not directly tackle the issue of misinformation detection. Furthermore, while research by Srba et al. [16] and Quan et al. [17] has examined the utilization of QAS platforms and term weighting schemes, respectively, they may not provide specific solutions for identifying and combating fake information. Therefore, there is a pressing need to develop tailored approaches that leverage advancements in data analysis, machine learning, and natural language processing to effectively identify and mitigate fake information within QAS platforms, addressing this critical gap in the literature and safeguarding the integrity of online information exchange."

3. Proposed Methodology

We have developed a new method called Squirrel Search-based Extreme Boosting (SSbEB) to detect and measure the severity of fake question and answers. Our boosting parameters have improved the accuracy of the algorithm, making it easier to identify the different stages of QA. Using this method, we were able to track and segment the features of the QA, and measure its severity score. We analyzed the accuracy of our QA prediction and severity estimation using performance metrics such as F-score, accuracy, precision, recall, and error rate. To illustrate our proposed architecture, please refer to fig.1.

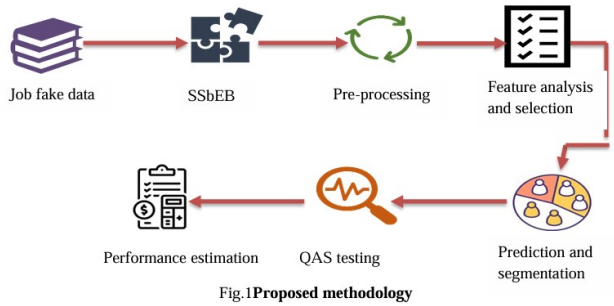

Fig.1**Proposed methodology**

3.1 Proposed SSbEB Working Functions

The presented solution framework has five different layers such as data importing, preprocessing, features analysis, optimal, and an output layer that is figured in fig.2. Here, the data training process has been executed in the input layer. The noise filtering process was performed in the hidden layers, then features extraction and Severity finding function in the classification phase of the SSbEB.

$$F(D) = D\{1,2,3,4,5.....n\} \quad (1)$$

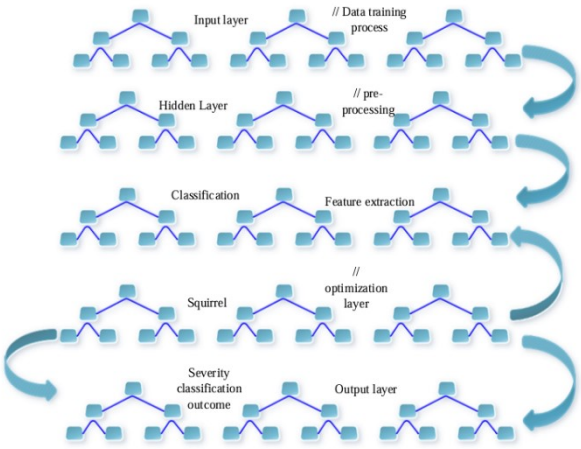

Fig.2 Layers of a novel SSbEB

Here, D represents the dataset, $F(D)$ denotes the training variable, and $1,2,3,4,5.....n$ represents the n number of data.

Besides, the proposed QA prediction and severity estimation system is processed based on the Extreme boost intelligent model [16] and squirrel algorithm [17]. To gain the finest severity specification outcome, the fitness function of the squirrel is given in the classification phase of the boosting model to tune the classification features that have gained the correct severity estimation outcome.

3.1.1 Pre-processing

The filtering process is the major function of the neural networks and imaging application to reduce the overfitting issues and to maximize the QA forecasting exactness score. Moreover, it has optimized the computational time and resource usage; hence, the preprocessing function was processed by eqn. (2).

$$H(D) = \frac{1}{2} D(y - e) \quad (2)$$

The preprocessing variable is determined as H, all raw databases contain normal and noise features. Hence, the noise features were represented as e, and the normal features are determined as y. By performing the eqn. (2) the noise features were eliminated from the trained database.

3.1.2 Feature analysis

To find the severity score of the predicted QA, the maximum level of present features was extracted using eqn. (3). Here v is the meaningless feature removed in this feature extraction function.

$$L = D(g_{max} - v) \quad (3)$$

The maximum related features in the fundus image are represented as g_{max}, and the feature extraction function is defined as L. Here, the features analysis function has been performed with the help of the squirrel fitness.

3.1.3 Fake QA prediction and segmentation

The trained database contains both normal and disease-affected images. Hence, the disease forecasting function has been performed to predict the abnormal QA and normal retina. The segmentation process has been performed to find the affected region and segment them. This disease prediction formulation is attained from the squirrel searching fitness that is equated in eqn. (4).

$$J = \begin{cases} if(L = 0) & normal \\ else & DR \end{cases} \quad (4)$$

Here, the disease prediction variable is represented as j. If the extracted features are equal to 1, it is recognized as QA. if the extracted feature count is 0, then it is normal.

Algorithm 1 SSbEB

Start

{

$int\, F(D) = 1,2,3,...n;$

// dataset initialization

Preprocessing ()

{

$int\, H, y, e;$

// pre-processing variables were initialized

$enable \rightarrow B$

// here, B is the boosting parameters

$B(H) \rightarrow filter(D)$

// noise filtering has been performed by eqn. (2)

}

Feature Analysis ()

{

$int\, L, g_{max}, v;$

// initiating feature extraction variables

$Extract = g_{max}(D)$

// extracting the required meaningful features

```
}
QA prediction ()
QA system ()
{
    int T, F, p, q
    //Initializing the QA system variables
    Matching → F(p,q) = T(p,q)
    // Suitable matched contents are retrieved
}
Topic modelling ()
{
    int G, a, b, c;
    // Topic selection parameters are initialized
    Topic=key words  matching
    //The topics for the selected keywords have resulted
}
}
Stop ()
```

4. Results and Discussions

The presented SSbEB technique is designed and tested in the Python environment. The execution of the SSbEB is processed by the job posting database gathered from the Kaggle site. The system was trained with the collected database and took some unseen test data from other databases.

We tested the effectiveness of SSbEB by using it in a Python environment on Windows 10. We measured its performance in terms of recall, error rate, accuracy, precision, and F-measure, and compared it to other methods like SVS, NB, DTM, LRA, BEM, and RFT [17]. We'll explain how each method performed in each metric.

3.1.1. Accuracy

Accuracy measures the retrieval of relevant answers for the tested question dataset. This metric validates the working efficiency of the proposed SSbEB system. The accuracy value calculation is expressed in Eqn. (6).

$$Accuracy = \frac{correct \quad Answers}{Total \quad Answers} \tag{6}$$

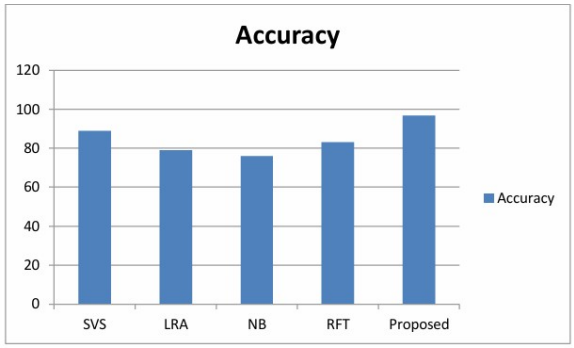

Fig.3. Accuracy Comparison

The accuracy rate compared with the existing methods is shown in Fig. 3. Here, the existing model SVS attained 89% of accuracy, and the other prevailing techniques like LRA, NB, RFT, and DTM achieved an accuracy rate of 79%, 76%, 83%, and 76%. Additionally, the BEM scored 86% accuracy in the relevant answer-retrieving process. Besides, the proposed SSbEB scored a higher accuracy rate of 96.6% in overall accuracy comparison. Hence the recommended system effectively retrieves the relevant answers for the searched job queries.

3.1.2. Error rate

The error rate measures the irrelevant answers obtained during the testing of the SSbEB model for the tested input questions. It is also one of the metrics to quantify the performance of the designed SSbEB system. The system performance is further enhanced based on the value attained for the error rate. The error rate calculation is shown in Eqn. (7).

$$Error = \frac{irrelevant \ answers}{\text{Total} \quad \text{Answers}} \tag{7}$$

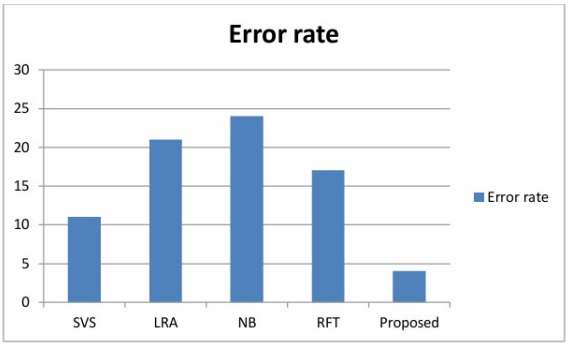

Fig.4. Error Rate Comparison

The error rate of the existing schema, such as SVS, LRA, NB, RFT, DTM and BEM, is 11%, 21%, 24%, 17%, 24%, and 14%. At the same time, the presented technique scored an error rate of 4.0%. The error score of the presented technique is lower than the other related models, which shows the better efficiency of the proposed model. The error rate comparison is illustrated in Fig. 4.

3.1.3. Recall

It is the measure of the accuracy ratio in the total relevant answers. It shows how accurately the designed model has predicted the relevant answers for the searched questions. The recall value calculation is shown in Eqn. (8).

$$\text{Re}call = \frac{tp}{tp + fn} \tag{8}$$

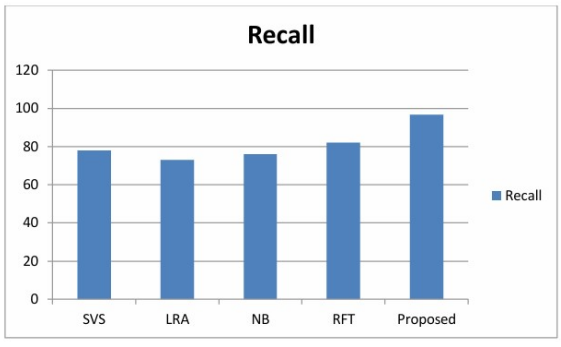

Fig.5. Comparison Of Recall Measure

The comparison recall rate is shown in Fig. 5. The existing scheme SVS scored a recall rate of 78%, LRA scored 73%, NB classifier scored 76%, RFT gained 82%, DTM resulted in 71%, and BEM achieved 82%. The proposed approach gained a recall rate of 96.7%. The proposed approach gained a higher recall rate than these current models.

3.1.4. Precision

The correct relevant answers that are retrieved among the relevant and irrelevant question datasets are termed precision. The precision value can be calculated by the Eqn. (9)

$$\text{Pr}ecision = \frac{tp}{tp + fp} \tag{9}$$

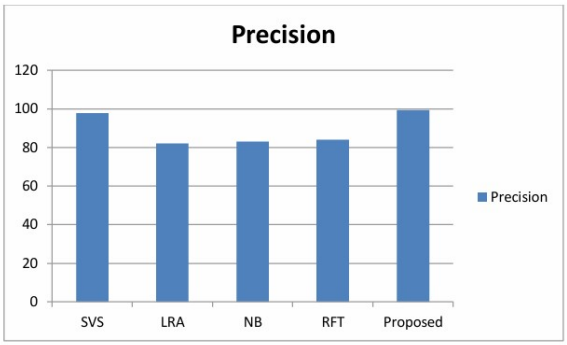

Fig.6. Precision Score Comparison

The precision rate comparison is shown in Fig. 6. Here, the method SVS scored the precision value as 97.6%, LRA scored 82%, NB achieved 84%, RFT gained 83%, DTM scored77%, and the technique BEM scored 87%. While the designed scheme achieved a precision rate of 99.6%, this is higher than the other existing method's precision score.

3.1.5. F-measure

It is the combined value of both recall and precision metrics. The mean value of the recall and precision score is obtained by calculating the f-measure. The expression for the f-measure calculation is shown in Eqn. (10).

$$F - measure = 2 \times \frac{recall \times precision}{recall + precision} \tag{10}$$

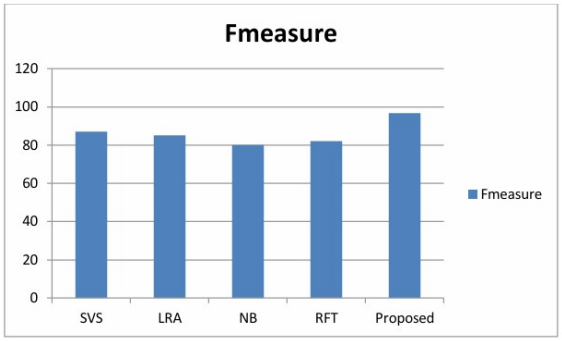

Fig.9. F-Measure Comparison

The f-measure comparison is shown in Fig. 7. In this figure; the SVS method scored 87% as the f-measure rate. The existing methods, like RFT and BEM, scored the f-measure value 82% and 77%. Moreover, the LRA method scored 85%, NB gained 80%, and DTM achieved 74%. Besides these methods, the proposed scheme achieved an f-measure rate of 96.6%. Comparing the related existing schemas, the SSbEB attained the higher f-measure rate. The overall comparison statistics are shown in table.1.

Table.1. Overall Statistics

Metrics	SVS	LRA	NB	RFT	DTM	BEM	Proposed
Recall	78%	73%	76%	82%	71%	82%	96.7%
Accuracy	89%	79%	76%	83%	76%	86%	96.6%
Precision	97.6%	82%	84%	83%	77%	87%	99.4%
Error	11%	21%	24%	17%	24%	14%	4.0%
F-measure	87%	85%	80%	82%	74%	77%	96.6%

3.2. Discussion

The presented system has shown enhanced accuracy for the relevant answer retrieval process and the topic modelling session. The overall results of the suggested SSbEB framework are recorded in table.2. The suggested system performed as an effective framework for the job assistant system in the big analytics data.

Table.2. Outcome Of REGM

SSbEB performance	
Recall (%)	96.7
F-measure (%)	96.6
Precision (%)	99.6
Accuracy (%)	96.6
Error rate (%)	4.0
computational time (s)	4.0

The given results validated the effective performance of the designed SSbEB. In this system, the extended feature learning during training function makes the system capable of answering web-based questions with greater accuracy. Also, the computation time of the answer retrieval process is recorded as 4.0 sec.

4. CONCLUSION

A novel SSbEB was structured for the efficient topic modelling question-answering system in the presented research. Initially, the job QA dataset is imported into the system. In the preprocessing stage, the noise from the input data is removed, and then the question words and keywords are analyzed from the feature extraction stage. Further, the relevant answer was retrieved for searched web-based questions based on the extracted features and the Topic modelled for three answer keywords. The system resulted from a 96.6% accuracy rate for the relevant answer retrieval with a lesser error rate of 4.0%. Compared to existing techniques, the accuracy improvement percentage is 2%. Also, the computation time is reduced to 4.0s. Additionally, the results of the metrics like precision, f-measure and recall have shown greater improvement from the existing models. Hence the presented QA system is suitable for the job assistant for searching the web-based questions. In future, QA system will improve with efficient optimization for the assistance in job assistance system.

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