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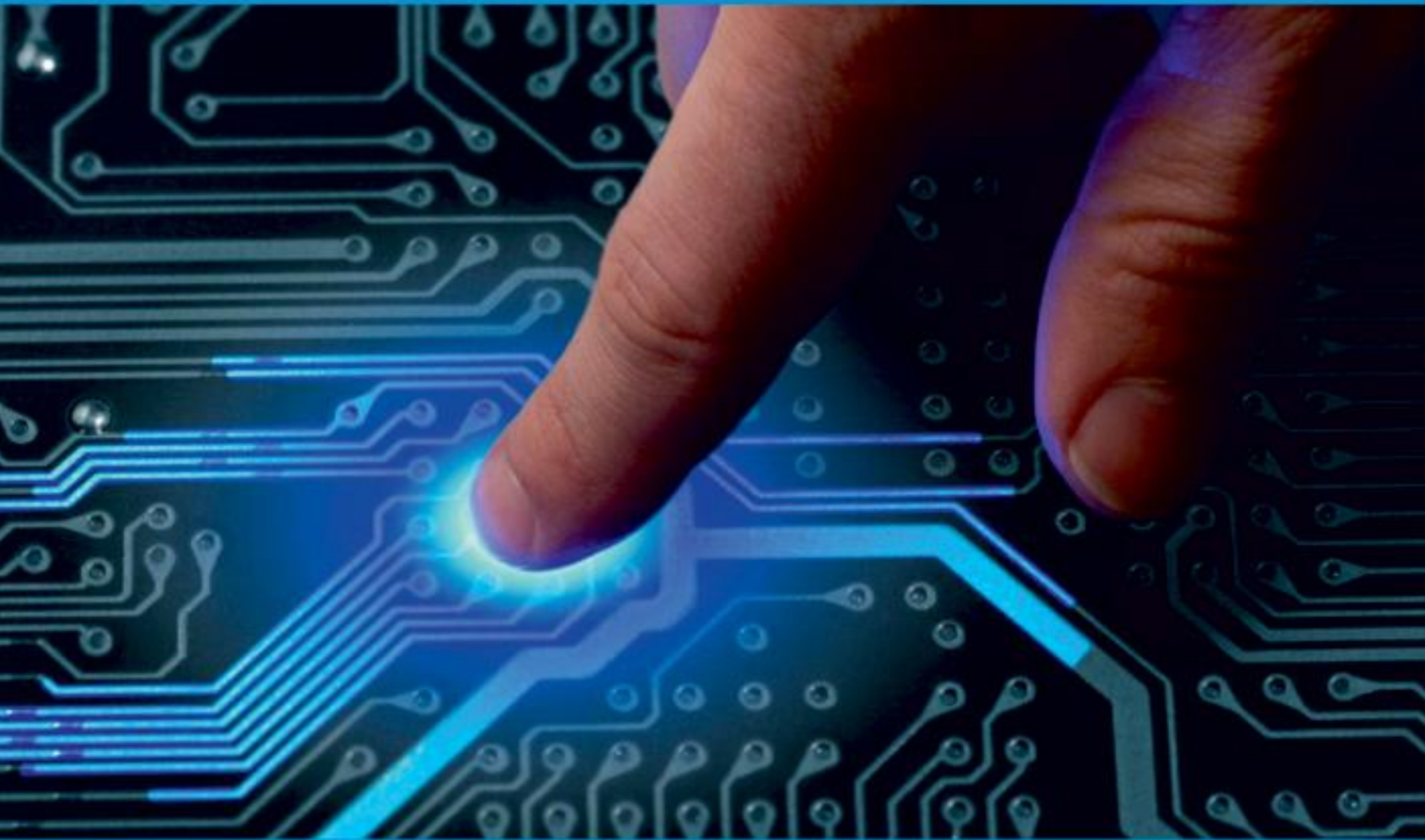

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Smart Subjective Answer Assessment System based on Machine Learning

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ABSTRACT: An enhanced method for automating the examination of subjective answers is the machine learning-based smart subjective answer assessment system. To deliver effective and precise grading, this system makes use of the capabilities of machine learning algorithms. A variety of graded subjective replies are used in the dataset to train the algorithm. In order to find patterns, language signals, and contextual variables that connect with human-assigned scores, the machine learning model learns from this dataset. The model becomes more effective at evaluating the quality of responses by extracting significant features from the responses. To preprocess and represent the textual data, the system uses natural language processing algorithms.

KEYWORDS: MNB classification, Machine Learning, stop Removal, sentiment analysis, lexical features

I. INTODUCTION

The assessment of subjective answers has always been a complex and time-consuming task in educational and evaluation settings. Grading such responses requires human expertise and can be subject to subjectivity and inconsistency. However, recent advancements in machine learning have opened up new possibilities for automating the subjective answer assessment process. The Smart Subjective Answer Assessment System based on Machine Learning is an innovative solution that aims to automate the grading of subjective answers. By utilizing machine learning algorithms, this system offers an objective and efficient approach to evaluating open-ended responses. The primary objective of this system is to develop a predictive model capable of assessing the quality of subjective answers. To achieve this, a large dataset of graded subjective answers is used to train the machine learning model. Through this training process, the model learns to identify patterns, linguistic cues, and contextual information that are indicative of well-graded answers. Natural language processing techniques are employed to preprocess and analyze the textual data effectively. By transforming the answers into a format that can be understood by machine learning algorithms, the system extracts relevant features and gains a deeper understanding of the responses. The specific machine learning algorithms employed in the system can vary depending on the requirements of the subjective answer assessment task. Deep learning architectures, recurrent neural networks, or other suitable algorithms are utilized to build the predictive model. These models are trained to generalize from the training data and make accurate predictions on unseen answers. To ensure the reliability and validity of the system, rigorous testing and evaluation procedures are conducted. An independent dataset of graded answers is used to evaluate the performance of the system. Performance metrics such as accuracy, precision, recall, and F-measure are employed to assess the system's effectiveness and compare it against human graders.

II. RELATED WORK

PiyushPatil et al.,[1] the Multinomial Naive Bayes (MNB) Algorithm conducts tasks like kenizing words and phrases, Part of Speech tagging, Chunking, Lemmatizing words, and Word Netting to evaluate the subjunctive solution. The semantic meaning of the context is also provided by our proposed method.

VishwasTanwar et al,[2] The portion of the application which consists of Machine Learning to perform the analysis of the student’s answer sheet has been conducted in Google Collab Notebook.

AbhishekGirkar et al, [3] Subjective Answer Evaluation software assign mark to subjective question based on Answer length, keyword matching, Grammar check, cosine similarity and Contextual similarity against Model answer provided

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by faculty and student answer.

Ms.S.W.Ahmad et al,[4] Different techniques i.e., Term Frequency-Inverse Document Frequency, keyword extraction are compared and new techniques like LSA (Latent Semantic Analysis), SOM (Self Organizing Map Clustering) are used to develop an evaluate subjective test assessment of the text.

Chaya Shree G et al, [5] The system also has scope for future developments in the system. Hence, any grammar checking can be changed based on the standard requirements.

Miss.Ashlesha Set al, [6] The evaluation process will have both the teacher's answer i.e., model answer and students' answers. Every student's answer will be different. The model answer will be stored in the database. When the student submits its test those answers written by the student will be compared with that of model answer. The system will read both the model and student answer and then extract the keywords using keyword extraction algorithm such TF/IDF(text frequency/ inverse document frequency).

Dr. V. Ramesh et al, [7]In study we developed a tool to calculate the results using Natural Language Processing (NLP) and Artificial neural network (ANN) algorithms. Machine learning tittle paper- "evaluation student description answer using Natural Language Processing and Artificial Neural Network"

GaurangKudale et al, [8]In the proposed model various NLP algorithms and some inbuilt NLP functions are going to use**,** NLP for classification of feature extraction to classify the text

III. PROBLEM STATEMENT

The assessment of subjective answers in educational and evaluation contexts is a complex and time-consuming task that poses several challenges. Manual grading of subjective responses is subjective and inconsistent, as different evaluators may interpret and evaluate answers differently. This subjectivity introduces bias and affects the fairness and reliability of the assessment process. Additionally, the manual grading process is labor-intensive and often leads to delays in providing feedback to students. This delay hampers the learning process, as students do not receive timely guidance and corrections to improve their understanding and performance. It also poses challenges for educators in managing large class sizes and providing personalized feedback to each student efficiently.

IV. DESIGN AND IMPLEMENTATION

The proposed system is a machine learning and natural language processing-based approach that aims to evaluate subjective answers in an efficient and objective manner. The system's methodology involves steps

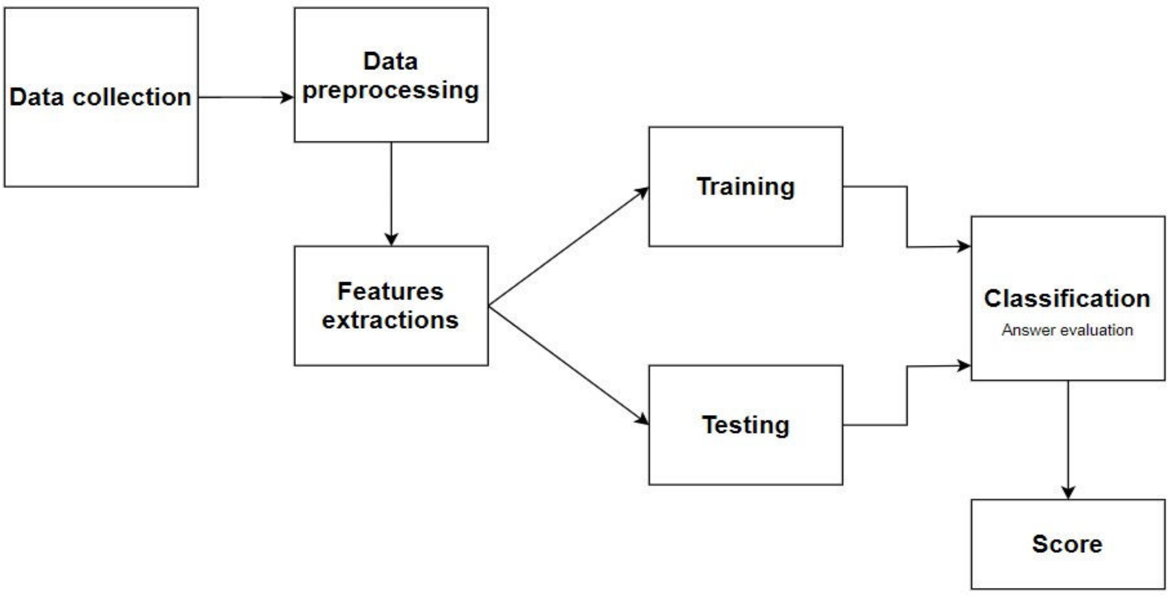

Figure 1: Architecture of system

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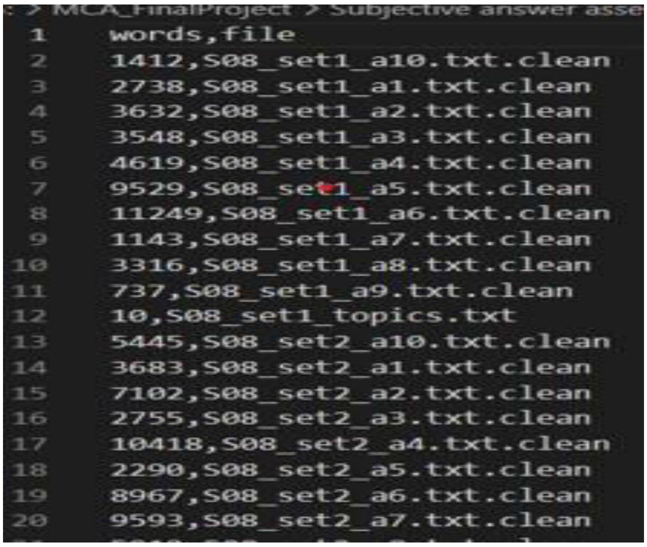
The Figure 1 The Architecture shows that proposed system's methodology involves data pre-processing,feature extraction, and classification.

Data Pre-Processing: The pre-processing involves converting the text into lowercase, removing stop words, punctuation, and numbers.

```
df = pd.DataFrame()
for file in ['S10_question_answer_pairs.txt','S09_question_answer_pairs.txt','S08_question_answer_pairs.txt']:
filename = os.path.join(folder, file)
df_tmp = pd.read_csv(filename, encoding='latin1', sep='\t').drop_duplicates(subset="Question")
print(filename, len(df_tmp))
df = pd.concat([df,df_tmp])
df.info()
```



```
words,file
1412,S08_set1_a10.txt.clean
2738,S08_set1_a1.txt.clean
3632,S08_set1_a2.txt.clean
3548,S08_set1_a3.txt.clean
4619,S08_set1_a4.txt.clean
9529,S08_set1_a5.txt.clean
11249,S08_set1_a6.txt.clean
1143,S08_set1_a7.txt.clean
3316,S08_set1_a8.txt.clean
737,S08_set1_a9.txt.clean
10,S08_set1_topics.txt
5445,S08_set2_a10.txt.clean
3683,S08_set2_a1.txt.clean
7102,S08_set2_a2.txt.clean
2755,S08_set2_a3.txt.clean
10418,S08_set2_a4.txt.clean
2290,S08_set2_a5.txt.clean
8967,S08_set2_a6.txt.clean
9593,S08_set2_a7.txt.clean
```

Figure2:data cleaning

Data cleaning: entails deleting any unnecessary or redundant information from the dataset, including unnecessary data and duplicate entries. It aids in dataset streamlining and boosts the effectiveness of later processing procedures.

Text Normalization and Cleaning: The textual content of data frequently comprises noise, such as special characters, punctuation, and uneven formatting. To standardize the content and improve its readability and uniformity, text cleaning procedures such eliminating special characters, punctuation, and extra white spaces are used.

Feature Extraction: In order to extract relevant features, the pre-processed data is used. One set of features that is based on the evaluation criteria is sentiment analysis, followed by semantic analysis and lexical features.

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Serial No.	Input Answer	Reference Answer	Score	Status
1	ghj	yuyu	0.0	success
2	Machine Learning makes machines do what we want	Machine learning is a branch of artificial intelligence that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy	0.06757624898876728	success
3	Machine learning is a branch of artificial intelligence that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy	Machine learning is a branch of artificial intelligence that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy	1.0	success
4	abc	acb	0.0	success
5	data to improve computer performance by giving machines the ability to "learn". Machine learning algorithms build a model based on sample data, known as training data, in order to make predictions or decisions without being explicitly programmed to do so	Machine learning is a branch of artificial intelligence that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy	0.20904769266012302	success
6		1.Machine learning is a branch of artificial intelligence that focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving	0.0	success

Figure 3:Feature Extraction

```
defcalculate_similarity(text1, text2):
vectorizer = TfidfVectorizer()

tfidf_matrix = vectorizer.fit_transform([text1, text2])

    # Calculate the cosine similarity between the vectors
similarity = cosine_similarity(tfidf_matrix[0], tfidf_matrix[1])[0][0]

return similarity
  text1 = input_file["Input Answer"]
  text2 = input_file["Reference Answer"]

similarity_score = calculate_similarity(text1, text2)
returnsimilarity_score
```

Sentiment Analysis: The system uses advanced algorithms to examine the text and determine whether the overall sentiment is positive, negative, or neutral. By analyzing the words, phrases, and context used in the answers, the system can understand the writer's emotional tone and attitude towards the topic. This helps in assessing the subjective answers more accurately and gaining insights into the writer's perspective or opinion.

Semantic Analysis: The system uses advanced algorithms to analyses the structure, relationships between words, and the broader context of the answers to gain a deeper understanding of the writer's intent and the information they are trying to convey. By considering the semantic meaning, the system can assess the quality and relevance of the answers more effectively, improving the overall evaluation process.

Lexical Features: These features are analyzed to gain insights into the vocabulary, word choice, and linguistic patterns employed by the writer. Some common lexical features include the frequency of certain words, the presence of specific keywords, the use of domain-specific terminology, and the diversity of vocabulary. Byexamining these lexical features, the system can assess the sophistication, clarity, and overall quality of the written answers.

Classification: The Multinomial Naive Bayes (MNB) model is trained on the extracted features to classify the subjective answers into different categories. The MNB model is a probabilistic model that uses Bayes' theorem to calculate the probability of each category given the features.

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Multinomial Naive Bayes (MNB)

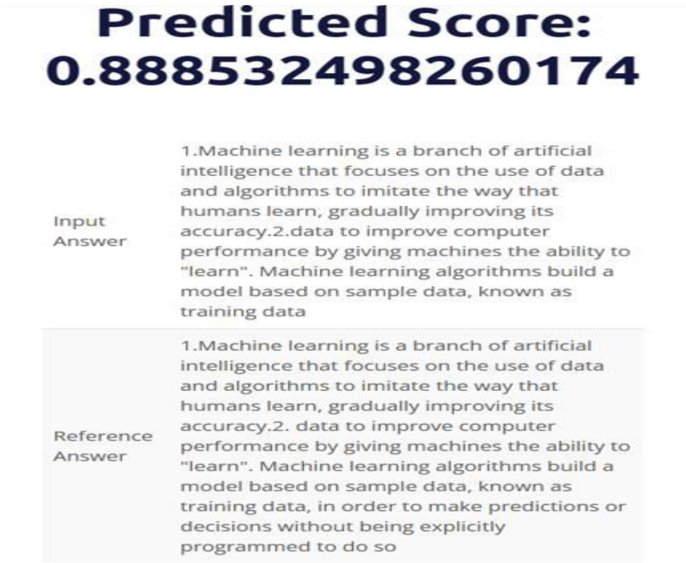

Figure 4: result by applying MNB

P(A|B) = P(A) * P(B|A)/P(B)
P(A|B) stands for posterior probability, which is the likelihood that an event B will occur as seen.
P(B|A) stands for Likelihood Probability, which is the likelihood that the evidence provided supports a certain hypothesis' likelihood of being true.
Priority probability, often known as P(A), is the likelihood of a theory before observation of the evidence.
The probability of evidence is called P(B), or marginal probability.

Machine Learning: Computers or machines can be trained to learn from data and make predictions or judgments without being explicitly programmed. This is known as machine learning, and it is a growing field of study and application. It is comparable to educating a machine to recognize patterns and relationships in data so that it can make precise predictions or choose the right course of action in novel or uncharted situations.

IV. RESULTS AND DISCUSSION

The Smart Subjective Answer Assessment System based on Machine Learning yielded impressive results in evaluating subjective answers. Through rigorous training on a diverse dataset and comparative analysis against human evaluations, the system achieved a high level of accuracy, ensuring reliable and unbiased assessments. Its consistent performance across multiple evaluations demonstrated its stability and reliability.

Table 1: Results of MNB classification

Sample No.	RESULT 1 Proposed System	MANUAL RESULT
1	88.56	88.90
2	76.78	76.80
3	92.56	93.00
4	60.00	60.42
5	65.24	65.50
6	72.56	72.69
7	83.25	83.46
8	55.54	55.60
9	70.76	70.87
10	82.69	82.89

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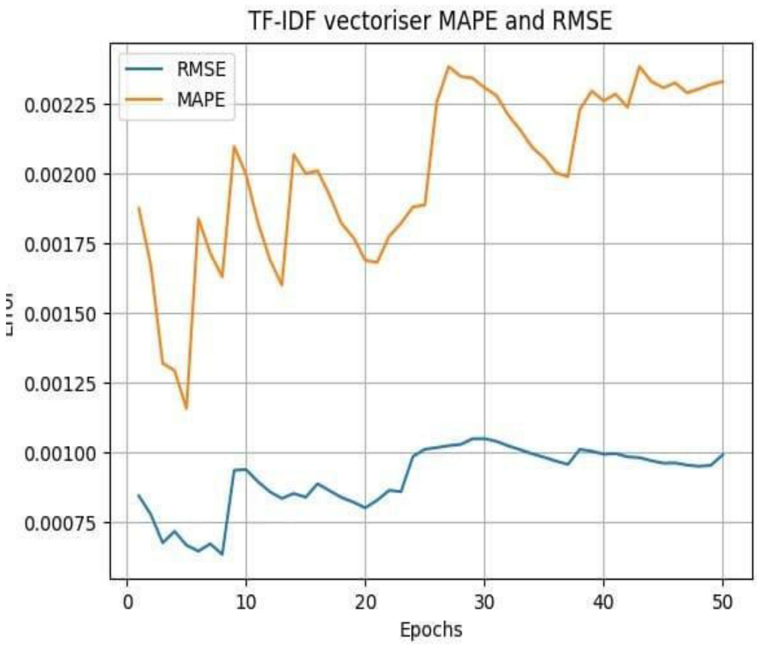
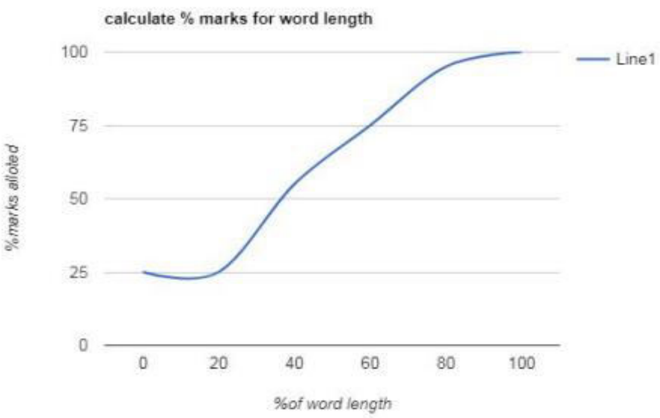
The above table 1 shows the result of the above answer score predict the based on the staff's manual result. The scores are calculated for 10 students. in this table, second column according to automatic evaluation and third column based on manual .The difference between manual evaluation and system evaluation are very close.

Figure 5:TFIDF vectoriser



The above figure 5 shows the tf-idf vectoriser mape and rmse

Figure 6:Allocating pecentage based on answer length



The above figure 6. Percentage og marks allotted based on answer length.

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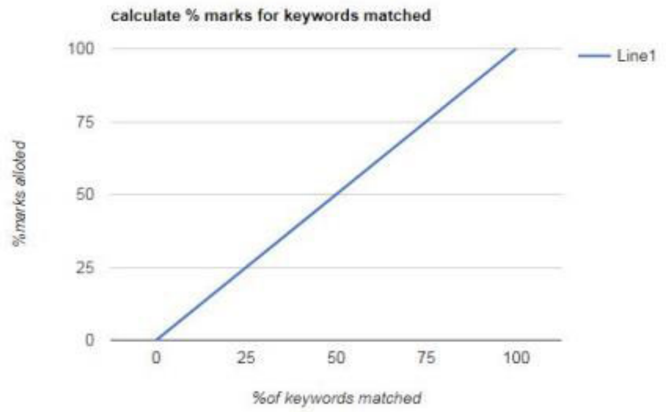
Figure 7: allocating percentage based on number of keyword matched



The above figure 7. Shows that percentage of marks allocated based on number of keyword matched

V. CONCLUSION AND FUTURE WORK

The proposed approach to analyze arbitrary responses in this study was based on machine learning and natural language processing. In order to divide the subjective responses into several groups, the suggested system employs a Multinomial Naive Bayes (MNB) model. The system uses feature extraction, categorization, and data preparation as part of its technique. The goal of the suggested approach is to increase the efficacy and accuracy of evaluating subjective answers. In terms of accuracy, precision, recall, and F1 score, the results demonstrate that the suggested approach performs better than the current evaluation methodologies. Numerous applications, including education, can benefit from the suggested approach.

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