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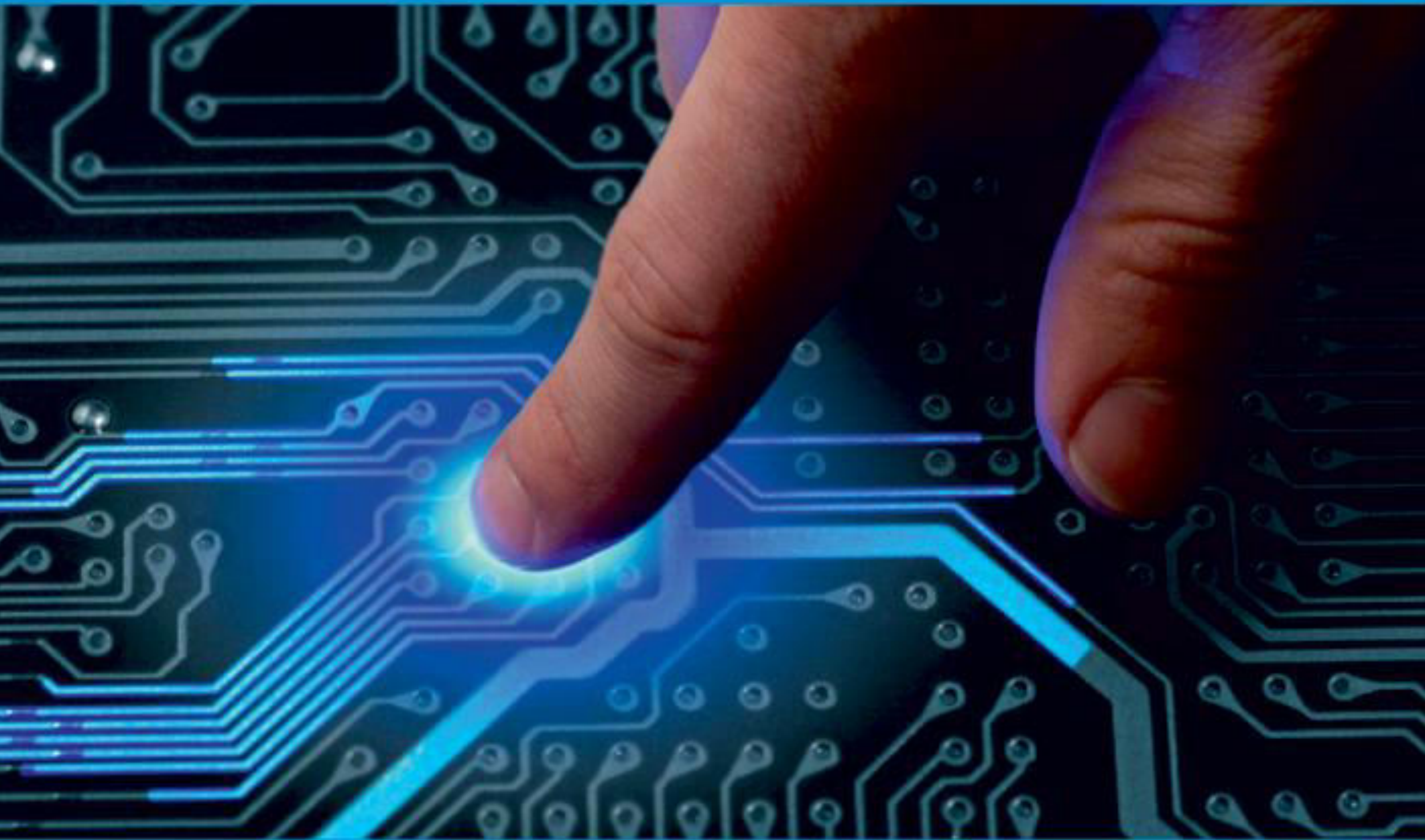

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A Review on Smart Examination System

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ABSTRACT: Testing is a busy process. The test is intended to measure the tester's knowledge, ability, competence, and more. The traditional test method is expensive, requires resources, too time-consuming. Questionnaire preparation, critical response generation, good test management, and standardized testing are all major tasks involved in managing successful testing. Setting up question papers takes a long time and requires the work of a skilled person. The same can be said of the answer key. Grading feedback by hand takes a lot of time, money, and other resources. Another problem the organization has with current infrastructure is air tests. Also of concern is the general review of response pages, which will remain subject to human bias in the current situation. Using state-of-the-art machine learning, natural language processing, and web technology, we work to overcome this challenge by building an automated testing platform. Our goal is to provide an inexpensive alternative to the current trial system.

I. INTRODUCTION

Education has evolved much over the recent few years. The impact of the COVID-19 pandemic has given rise to a new way of teaching and education by making everything online. With the technological advancements, it is now easier for students to learn and teachers to conduct learning sessions efficiently. But in between all these, the problem of conducting examination and evaluating fairly remains constant. The traditional system relies on manual paperwork from setting the questions to printing & transporting the paper, then conducting the examinations without cheating.

However, few online examination systems have been introduced which include multiple-choice types of questions that limit the scalability of any examination. Our work aims to build an examination system that offers an online software platform that generates multiple-choice types as well as subjective types of questions automatically and evaluates the result itself. The purpose is to achieve more accuracy, efficiency, and reliability and to reduce the resource and time cost for all examination conduction. This will eliminate the burden of human error and bias.

II. RELATED WORKS

The purpose of the literature review was to learn more about previous research on question generation, answer evaluation and to study the existing technologies and algorithms for Natural Language Processing and examination systems that are already in use.

1. The work "Examination System Automation" by Indrashis Das, Bharat Sharma, Siddharth S., and Manjusha Pandey presented and introduced a paper keyword extraction from text. It involved conducting tests using a few algorithms at regular intervals that the trend in the marks obtained by different students can be determined and reports can be analyzed on the different subjects they need to focus on for which they are weak.
2. Hussein Al Bazar proposed an algorithm to distribute a form that prevented the system from producing test sets that could be duplicated and shared among close students. This was to ensure that no two candidates get the same type of questions.

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III. OUR MODEL

It is a method that helps to analyse and find out the most important and relevant keywords in the sentence. It enables faster search and is helpful in combining similar text and also to find quick answers and central theme. Keyphrase extraction is usually based on 2 principles. First, finding the same words and the second is finding words that are similar in meaning to the base word. This is achieved with the help of Id-tdf. It stands for term frequency-inverse document frequency. The term frequency counts the number of times the word appears in the document, and the idf computes the most important and useful words that can be used for analysing the document. The goal of tf-idf is to figure out how important a word is in a given document. The other model used is Elmo which is a deep conceptualized representation of a word. It finds out the meaning of words based on the context it is used, rather than depending upon the usual dictionary definition. It makes use of semantics, sentactics and word. It makes use of deep bidirectional language model(biLM), which consists of forward and backward LM. It makes use of large dataset to predict the next and previous words. In backward LM the Elmo is trained to predict the previous word given the next word. In forward LM the Elmo is trained to predict the future word based on the past word.

We measure TF-IDF scores using the following formula:

$$\mathbf{tf}(t,d) = \frac{f_d(t)}{\max_{w \in d} f_d(w)}$$

$$\mathbf{idf}(t,D) = \ln\left(\frac{|D|}{|\{d \in D : t \in d\}|}\right)$$

$$\mathbf{tfidf}(t,d,D) = \mathbf{tf}(t,d) \cdot \mathbf{idf}(t,D)$$

$$\mathbf{tfidf}'(t,d,D) = \frac{\mathbf{idf}(t,D)}{|D|} + \mathbf{tfidf}(t,d,D)$$

$f_d(t) :=$ frequency of term t in document d

$D :=$ corpus of documents

Elmo

Elmo word representation consists of various internal states of biLM. It uses all its internal states for embedding and uses the last layer for embedding vector. The higher layer outputs helps to capture more information and context whereas the lower level output focus on the syntax. In Forward LM the first word gets converted into character embedding which goes into the first LSTM cell. The LM will be trained to predict the next word using the current word. It may not be possible to predict the tense or the next word, hence backward LM is used. Backward LM helps to generate embedding precisely with the help of future words as a reference. Combing both these results in a better score.

Siamese LSTM

In a siamese neural network, we have two same sets of convolutional layers, that share the same filter. In this model we take up two different inputs and calculate the commonality and similarity between the two sets. The neural network helps to derive the feature vectors and combine the two together. The recombining of the vector is done by taking the absolute difference between each element. After recombination, the single vector is then sent through sigmoid function.

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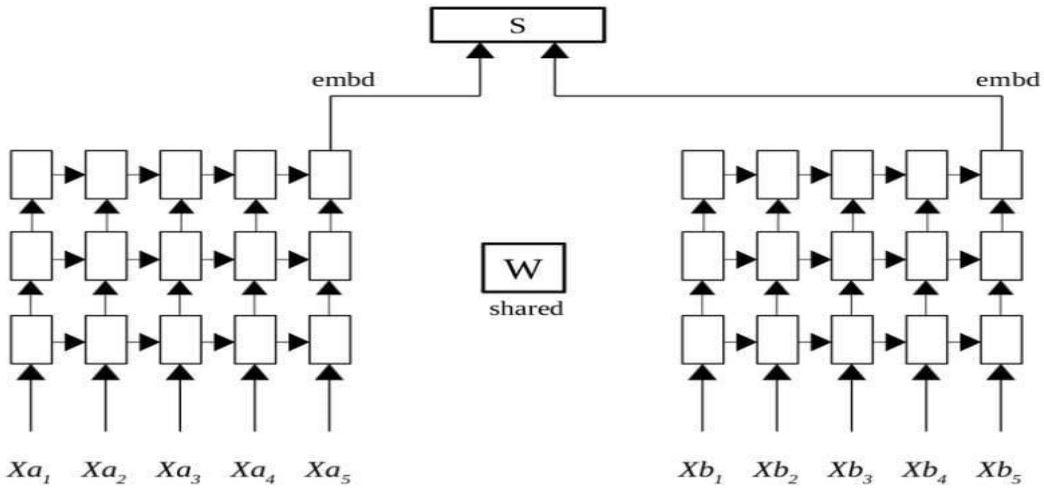
The function gives the output of the similarity score. The similarity between answers is calculated based on their similarities.



IV. FUTURE WORK

For future improvement LSTM is used for knowing the context of the text, to know its forward and backward nature. In particular, siamese LSTM will be used to generate a questionnaire of more relevance and accuracy to the context, the deep recurrent neural network will be used. The system could be taught to understand the mathematical terms and formulas which can be achieved by using a convolutional neural network.

The system could use hyper-parameters to refine quality phrases to entity mention and finally it could be customized to work with those languages without general knowledge for the purpose of generating an accurate question pool or surplus questionnaire from the corpus with noise refinement capabilities.

V. CONCLUSION

In this paper, we present an automated phrase mining framework for making the question-taking and answer correction method in examinations automatic. The system can be learned even by a novice with little or no prior knowledge required for the overhead. When given a corpus the system generates a questionnaire, which could be of two forms 1) multiple-choice or 2)subjective. It then analyses the questions to find answers to those questions themselves. After accepting the user's response it matches the answer and generates scores on basis of the match. We can simulate the subjective test to up to 89 percent of accuracy and the objective simulation to up to 97 percent. The system can be used by self- teaching and no extra resources other than a corpus are required for this. It can be run on a browser application.

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