Important Citation Identification by Exploding the Sentiment Analysis and Section-Wise In-Text Citation Weights

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ABSTRACT A massive research corpus is generated in this epoch based on some previously established concepts or findings. For the acknowledgment of the base knowledge, researchers perform citations. Citations are the key considerations used in finding the different research measures, such as ranking the institutions, researchers, countries, computing the impact factor of journals, allocating research funds, etc. But in calculating these critical measures, citations are treated equally. However, researchers have argued that all citations cannot be given equal weight. Therefore, researchers have proposed other techniques to identify the important content-based, meta-data-based, and bibliographic-based citations. However, the produced results by the state-of-the-art still need to be improved. In this research work, we proposed an approach based on two primary modules, 1) The section-wise citation count and 2) Sentiment based analysis of citation sentences. The first technique is based on extracting the different sections of the research articles and performing citation count. We applied Neural Network and Multiple Regression on section-wise citations for automatic weight assignment. The citation sentences were extracted in the second approach, and sentiment analysis was used for sentences. Citations were classified with Support Vector Machine, Multilayer Perceptron, and Random Forest. F-measure, Recall, and Precision were considered to evaluate the results, compared with the state-of-the-art results. The value of precision with the proposed approach was enhanced to 0.94.

INDEX TERMS Important citation identification, sentiment analysis, weight assignment, machine learning.

I. INTRODUCTION Scientific research always has its roots in the literature of the domain [1]. Citation specifies the relationship between the citing and cited articles. In the research community, citations act as an acknowledgment of the stat-of-the-art work and the researcher. Therefore, the citation is deemed as a gauge to measure the different research aspects such as the impact factor of journals [2]. H-index, I-index, research grants, and funds [3], awards, ranking of researchers [4], institutions, etc. To compute such parameters, all citations are given equal weightage. In this era, the researchers have asserted that each citation is not influential [5], and the importance of citations varies for reasons such as researchers can cite an article to provide technical background, enhance the results, or compare the findings. To analyze the citations, qualitative features should be accompanied by quantitative aspects. The research community suggests that a citation reflecting only literature knowledge and a citation that enhances the work can never be of equal importance. In research articles, citations...
are primarily made to provide the general background of the research work [6]. Therefore, researchers have adopted multidisciplinary approaches to discriminate between important and non-important citations. If a citation enhances the work, it is considered important and non-important in the case of providing only background knowledge [7].

The researchers have developed multiple models and approaches to classify the citations concerning their reasons. This classification was converted to automatic categorization by manually asking the reasons from the authors. Finney [8] was the first researcher who proposed an automatic model to classify citations into seven categories. The different groups of citations were merged, forming two classes such as important and non-important citations. The key approaches for the classification of citations are 1) Content-based [7], [9], 2) Meta data-based [10], 3) Count based [11], 4) Sentiment based [5], 5) Hybrid approaches [12], etc. In Meta-data based and Content-based techniques, the similarity of the corpus is calculated while the frequency of citation is considered in the count-based approach. Zhu et al. [9] performed the pioneer binary classification of citations. This work was enhanced by Valenzuela et al. [7]. The author utilized contextual features and categorized the citations into non-important and important categories. Qayyum and Afzal et al. [10] used the Meta-data approach and enhanced the results further. Wang et al. [12] introduced the syntactic and contextual-based approach. The author produced a 0.85 value of the F-measure. The produced results by the state-of-the-art need to be enhanced for potential decisions.

This research presents a hybrid approach to identifying the credible citations of research articles. To experiment, two annotated datasets were used. The first dataset was collected by Valenzuela et al. [7], and the domain experts annotated this dataset. The second dataset was compiled by [10] and annotated by a Faculty member of the Central University of Science and Technology Islamabad. To classify the citations, different modules were considered, such as 1) Citation Count, 2) Similarity of research articles, 3) Section-wise weights for in-text citation, and 4) Sentiment analysis of citations. In citation count, the direct and indirect frequency of citations was considered. Furthermore, a cosine similarity algorithm was utilized to calculate the text similarity of citing and cited research articles.

Further, the sentiment analysis on citation sentences was performed, and the citation was categorized as positive, negative, or neutral. Finally, a section-wise citation count was performed to assign the automatic weights to sections. Considering the section-wise citation count Neural Network and Multiple Regression algorithms were utilized to produce appropriate weights for sections. Support Vector Machine, Multilayer Perceptron, and Random Forest were considered to classify the citations. The performance of the approach was measured with Precision, Recall, and F-measure values. The produced results were compared with state-of-the-art. The outcomes of the experiments enhanced the state-of-the-art results from 0.9 to 0.94 value of the F-measure.

This research considered potential features for identifying important citations, such as section-wise in-text citation weights, sentiment analysis, and similarity of research articles. These features effectively classified the citations producing a significant value of the F-measure. As a result, the proposed approach outperformed as compared to the state-of-the-art making a considerable contribution to the literature.

II. LITERATURE REVIEW

Citations are the key factors in effectively estimating the different technical aspects, such as the impact factor of journals, H-index, and I-index. Citations represent the bond between the citing and cited research articles. The esteem citation analysis is used to acquire scientific information about the author’s research work. The pioneer of the domain citation analysis was Garfield [13]. The author worked on the correlation between citations and the Prize winners. Furthermore, Inhaber and Przednowek [3] developed the idea of considering the relationship between citations and research fund winners. Garfield [13] performed the research and extracted the 15 reasons for citations to find out why the authors do citations. These reasons were investigated by Bornmann and Daniel [2]. Moravishki and Murugesan [6] performed the citation classification based on the reasons. The author claimed that the citations are performed considering different reasons. Therefore, citations are not equally influential. The classification categories of citations were reduced to 13 by Spiegel-Rosing et al. [14]. In the early era of citation analysis, the reasons for citations were manually asked by authors. The manual citation reason finding was unfeasible for a massive corpus. Therefore, the need of the hour was to classify the citations automatically.

Roger Mayer et al. [15] explained that specific words or phrases with citations could justify citation category. Moravishki and Murugesan [6] introduced the citation classification technique and reported that a single citation could belong to different categories. Finney performed the first semi-automatic citation classification [8]. The author classified the citations into seven categories. The fully automated approach for citation classification was introduced by Garzone and Mercer [16]. The author highlighted the shortcomings of the Finny model. The citations were categorized into 35 categories using 195 lexical and 14 parsing rules for documents. The approach was implemented on a dataset of 20 research articles. The experiments showed better results on the known dataset, but for the unknown dataset, the results were averaged. Giles developed the first automatic citation indexing engine [17], later named CiteSeer. This engine is a digital library consisting of literature on computer science. Pham and Hoffmann [18] categorized the citations into four categories. Bi et al. et al. [19] proposed a similar approach. The author considered the direct and indirect citations. The author stated that the proposed system achieved higher results than a state-of-the-art method like SCi and PageRank. Another automated approach was introduced.
by Teufel et al. [20] based on a supervised machine learning model.

The author considered different linguistic rules and classified the citations into four groups. The citation groups were further divided into 11 subgroups. The dataset consisted of 548 citations, and these citations were categorized considering 892 linguistic phrases. A 90% dataset was utilized for training the model, and the model was tested on the remaining 10%. The results depicted that 65% of citations were neutral with a 0.71 value of the F-measure. Sugiyama et al. [10] classified the citation into citing and non-citing categories. The Support Vector Machine (SVM) model was considered to implement the approach, utilizing different features such as nouns, position phrases, following sentences, n-grams, and previous sentences. It was reported that context and proper nouns were significant for training purposes.

Agarwal et al. [22] used SVM and Naïve Based approaches to classify citations considering eight categories. The dataset used by the author consisted of 43 research articles from the domain of medical science. The annotation was performed with phrases from the context of citations. The results were presented in the form of an F-measure value of 0.76. Next, Small [23] performed the sentiment analysis of citations to understand the social process. The dataset of 20 research articles was used, consisting of words and phrases depicting the sentiments of citations. The author reported the correlation of sentiments with social and cognitive reasons. Finally, Shahid et al. [24] developed an approach to find the relevant research articles. The author used a dataset of 16404 reference pairs and stated that the articles would be relevant if the citation frequency were five or more. This approach was further enhanced by Hou et al. [25]. The author claimed that if the in-text citation frequency is more than 10, there would be vital relevancy between the citing and cited research articles. For this experiment, the dataset of 651 articles was used, and the results showed closely related references more often.

To classify the citations, Balaban [26] introduced the approach of assigning more weightage to the citations of famous authors. The author also stated that a research article would be significant if cited by the high impact factor article. Dong and Schäfer [27] reduced the classes to three, considering that more classes can produce a conflict for citations. The classes were 1) Positive, 2) Negative, and 3) Neutral. Athar [28] also classified the citations into three categories. Next, the author performed the sentiment analysis on citations. Citation analysis was further implemented by Jochim and Schütze [29]. Finally, the author proposed an approach to find the citations having more impact in the research domain. For this experiment, different lexical features from context were utilized, and the dataset was collected from ACL Anthology. Classification of citations into two categories was performed by Roger Mayers [15]. The author used a dataset of 20 articles. Another classification technique based on keywords was introduced by Kumar [30]. The citations were categorized into 1) Positive and 2) negative classes after performing sentiment analysis. The dataset was collected from Association for Computational Linguistics (ACL) Anthology.

Lee et al. [31] classified the citations into three categories 1) Positive, 2) Negative, and 3) Neutral. These categories were further distributed into 12 subcategories. The dataset consisted of 6,355 citations. To perform the experiment n-gram technique was used. The model achieved a 0.67 value of the F-measure. Butt et al. [32] proposed extracting the five sentences with citations. The author implemented sentiment analysis using Naïve Bayes to classify the citations. The accuracy of the model was 80%. The same research was conducted by Sula and Miller [33], and the author used the Naïve Bayes model to classify the citations. They manually extracted the citation sentences and annotated them as positive and negative citations. But the proposed model could not extract the multiple citations in a sentence. Another approach for the classification of citations was proposed by Kumar [30]. The approach was keyword-based. The citations were categorized as positive and negative citations. The dataset was collected from ACL Anthology.

Zhu et al. [9] classified the citations into two categories and termed them categories influential and non-influential. The author used the machine learning algorithm Support Vector Machine for the classification. The dataset consisted of hundred research articles collected from ACL Anthology. Five features were used: citation frequency, similarity, position-based, context-based, and miscellaneous. This research was further enhanced by Zhu et al. [9]; the author classified the citations into important and non-important citations. The dataset collected from ACL Anthology consisted of 465 pairs of citation articles. Field experts annotated the citations. The experts 93.6% agreed on classification. For classification, twelve features were utilized, such as citation count, similarity, direct, indirect, etc. The authors utilized SVM and Random Forest models while computing the value of precision as 0.65 and Recall as 0.90.

The results were further boosted by Qayyum and Afzal et al. [10], and citations were classified into two categories. For this experiment, two datasets were used. The first dataset was collected from the research work of Valenzuela et al. [7], and the other dataset consisted of 324 citation pairs. The Faculty of Computer Science, CUST Islamabad, collected and annotated this dataset. The research work was performed on metadata [34] of research articles. Eight different features were used, such as title similarity, abstract similarity, keywords similarity, etc. The author used three machine learning models SVM, KLR, and Random Forest. The author claimed the best results with Random Forest by achieving a 0.72 value of precision. Aljuaid et al. [5] enhanced this idea by considering the sentiment analysis and achieved a 0.83 precision value. After that, we [11] contributed to the citation classification domain and increased the results to 0.84. Currently, the state-of-the-art approach [12] has achieved a 0.9 value of precision, but considering the citation important is still not optimal.
TABLE 1. Dataset D1 statistics.

| Annotation     | Label  | Category | Citations |
|----------------|--------|----------|-----------|
| Related Work   | 0      | Non-important | 398       |
| Comparing Work | 0      | Non-important | 2046      |
| Utilizing Work | 1      | Important  | 67        |

TABLE 2. Dataset D1.

| Annotator | Papers | Cited by | Follow up |
|-----------|--------|----------|-----------|
| A         | J02-3001 | E03-1040 | 0         |
| A         | J02-3001 | P04-1043 | 0         |
| A         | J02-3001 | P07-1071 | 1         |
| B         | P05-1043 | D13-1191 | 0         |
| B         | P05-1043 | E09-1007 | 1         |

TABLE 3. Dataset D2 statistics.

| Annotation     | Label  | Category | Citations |
|----------------|--------|----------|-----------|
| Related Work   | 0      | Non-important | 216       |
| Comparing Work | 0      | Non-important | 95        |
| Utilizing Work | 1      | Important  | 95        |

TABLE 4. Dataset D2 titles.

| Sr # | Title                                           |
|------|-------------------------------------------------|
| 11   | Single-ISA Heterogeneous Multi-Core Architectures |
| 12   | JEOPARD – Java Environment for Parallel Real-Time Development |
| 13   | Experiments with Cholesky Factorization on Clusters of SMPs |
| 14   | A Parallel Java Grande Benchmark Suite           |

TABLE 5. Dataset D2 citation pairs.

| PaperID | CitedBy | Fine Grained Value |
|---------|---------|--------------------|
| 16      | 35      | 0                  |
| 16      | 36      | 0                  |
| 37      | 16      | 1                  |
| 38      | 16      | 0                  |

III. METHODOLOGY

To classify the citations into two categories, such as important and non-important citations, the overall approach is given in Figure 1. This experiment consisted of four key modules: 1) Similarity calculation, 2) Citation Count, 3) Section-wise weights assignment, and 4) Sentiment Analysis of citation sentences. Machine learning algorithms Random Forest, Multilayer Perceptron, and Support Vector Machine were used. The results were evaluated using Precision, Recall, and F-measure.

A. DATASET

This research was conducted considering two datasets. The first dataset was collected by Valenzuela et al. [7], and the other dataset was composed by Faiza Qayyum and Afzal [10]. Valenzuela’s dataset consisted of 20,527 scientific research papers. This dataset was obtained from ACL Anthology, and two experts in the domain performed the annotation of the dataset. The extracted number of citations was 106,509, and due to difficulty in labeling a massive number of citations, the annotators only considered 465 citation sets. The domain experts categorized the citations into four classes concerning their importance in articles. Further, the four groups converged into binary classes. In dataset, 0 represents non-important and important citations are reflected by 1. 14.6% of citations were annotated as non-important, and 85.4% as important, as presented in Table 1.

In Valenzuela’s dataset, the IDs of research articles are placed, and by using these IDs, the pdf files can be downloaded from http://www.aclweb.org/anthology/. The IDs will be linked at the end of the Anthology URL to extract the Pdf files. The annotated dataset is shown in Table 2. Unfortunately, while performing the scraping, IDs 1) L08-1584, 2) W07-2058, 3) L08-1267, and 4) L08-1584 were unavailable, and four ID were unable to be scrapped. Therefore, 457 research articles were considered from the first dataset for the experiment.

In the first column of Table 2, A and B represent the annotators. The following field presents IDs of cited research papers; the third column consists of citing research papers.

Finally, the fourth column describes whether the citation is important or not. Here, 0 is presenting a non-important citation, and 1 is for an important citation. To increase the citation pairs, we considered another dataset consisting of 324 research articles and 311 citation pairs.

The research papers were from several publishers such as IEEE, Elsevier, Science Direct, etc. This dataset was gathered by [10] and annotated by the members of the Faculty of Central University of Science and Technology (CUST) Islamabad. As described in Table 3, most of the citations were from non-important citation classes, and important citations were more minor in number. This dataset contained two spreadsheets, the first sheet comprised the titles of research articles and their IDs and the second sheet had follow-up of citation pairs, describing if the citation is important or non-important. The dataset D2 is presented in Table 4 and Table 5. These tables consist of Titles and citation pairs.

B. PDF TO TEXT CONVERSION

The research articles of dataset D1 were automatically downloaded from Anthology, considering their IDs. On the other hand, for dataset D2, we manually downloaded the articles from different publishing sites. All the research articles were in PDF format. PDF files store the text in the form of a content stream, and parsing the PDF files is a difficult task to perform. In comparison, Text files are the simplest document form and can be easily parsed. Therefore, both datasets’ PDF files were converted into Text files. To perform this conversion XPDF tool was used, which is openly available on GitHub. This tool implements the R language and is considered efficient for such conversions. Therefore, using XPDF1 the PDF files were automatically converted into Text files.

1https://github.com/kermitt2/xpdf-4.00
C. CONTENT EXTRACTION
After converting the PDF files into Text files, the content extraction from Text files was performed. Therefore, text files were parsed using an openly available tool ParCit [35], and can be downloaded from the GitHub site. This tool uses a Conditional Random Field Model and is already trained. Therefore, we do not need to train it. It performs tokenization at the sentence level and labels the tokens. It considers different research elements such as (1) Title, (2) Authors, (3) Abstracts, (4) Different Sections, and (5) citations. This tool parses the files considering their structure and can extract bibliographic portions. The text files of datasets D1 and D2 were parsed, and different elements of files were extracted.

D. CITATION IDENTIFICATION
It is a complex task to identify the citation location as the citation styles vary concerning publishers, but in both datasets, the citation pattern was similar. Therefore, the identification process became feasible. For citation identification, the sections were parsed, and the program automatically located the citations. First, for each citation pair, the Authors name and the publishing year were the main elements for locating the citations. Next, the structure of citations was considered as it starts and ends with round brackets. Then, the publishing year and name of the author in citation were compared with articles publishing year and author of articles. Finally, this pattern matching was executed for each section, and the citation locations were identified. The identified citations were further utilized in calculating overall citations of manuscript, section-wise citations and in citation sentence extraction for performing sentiment analysis.

E. SECTION-WISE WEIGHT CALCULATION FOR IN-TEXT CITATION
The section-wise weight calculation phase consists of two sub-modules, 1) calculating section-wise citation count and 2) Assigning weights to sections. In this step, we identified the section-wise citation and counted the citations concerning the sections. After that, we used machine learning algorithms to assign weights to sections. Four sections were considered that are a standard part of most of the research articles such as 1) Introduction, 2) Literature Review, 3) Methodology, and 4) Results and Discussions.

1) CALCULATING SECTION-WISE CITATION COUNT
The frequency of citation can be termed as its occurrences in a specific research article. This approach is quantitative and simple, where the frequency of citation is considered. For example, if a research article is cited three times, the citation frequency will be three. To calculate the section-wise citations, we considered four key sections [36] 1) Introduction, 2) Literature Review, 3) Methodology, and 4) Results and Discussions. Then, considering citation pairs, the citations were computed. Table 6 presents the section-wise citation count for dataset D1.

2) WEIGHT ASSIGNMENT TO SECTIONS
For automatic weight assignment, we used supervised machine learning models 1) Neural Network and 2) Multiple Regression. Many researchers used these models to calculate the weights. For example, Karakaya and Awasthi [37] proposed an approach for relative weight calculation using Multiple Regression. Multiple Regression considers a single dependent feature and multiple independent features. Similarly, Neural Network was utilized by Choi et al. [38] for landslide susceptibility analysis. Therefore, we focused on Multiple Regression and Neural networks for weight calculation.

F. SENTIMENT ANALYSIS
The sentiment analysis provides the intent of citation, whether the document is positively or negatively cited. The positively cited citations would be more probably important ones. In this phase, we extracted the sentences with citations and performed sentiment analysis to explore the essence of citation. This step consists of three modules. In the first module, we select the window size for citation sentences.
In the second step, we performed the sentiment analysis, and thirdly, the sentiment score was calculated.

1) SELECTING WINDOW SIZE
For sentiment analysis, different citation windows can be considered, such as 2-3 sentences across the citation, a single sentence after, and a single sentence before the citations, or it can be one sentence where the citation is present. We selected the window size 1, considering the sentence where citation occurred as this approach is termed better than other approaches [39]. Next, the citation sentence was extracted using in-text citation identification. The citation sentence extraction consisted of the following steps:

- Identification of the citation using in-text citation identification.
- The existing text before opening brace was picked till the full stop of the last sentence appeared.
- The after the text of closing brace was picked till the full stop of this sentence.
- Storing the picked sentence in comma-separated values (CSV) file.

2) CITATION SENTIMENT ANALYSIS
To classify the text, sentiment analysis was used. Different machine learning algorithms exist for text classification, but the model produces better results. Therefore, the commonly used classifiers were evaluated, such as Multinomial Naïve Bayes, Support Vector Machine, Random Forest, K-Nearest Neighbour, and Logistic Regression. Finally, the model that produced high accuracy and a high average macro score was selected for the classification of citations into Negative, Positive, and Neutral categories. The process is represented in Figure 2.

3) TRAINING DATASET
To train the models, a training dataset was used that was collected by [23]. This dataset consisted of four features, 1) Source_Paper_Id, 2) Target_Paper_ID, 3) Sentiment and 4) Citation_Text.

The first feature contains the ID of the cited research articles, while the second feature shows the IDs of citing research articles. In the Sentiment feature, ‘p’ reflects the positive, ‘n’ represents negative, and ‘o’ represents neutral or objective sentiments. The last feature contained the text having the citation sentences. This dataset was given as input to the state-of-the-art machine learning models. The summary of the training dataset is presented in Table 7.

4) PRE-PROCESSING
Preprocessing is important while manipulating the text or performing text classification. In this step, we tokenized the sentences and then converted those tokens into lower case. After that, the tokens were labeled using parts of speech (POS) tagging. Finally, the stop words were removed from the text, and lemmatization was performed. This preprocessing was conducted using Wordnet and Natural Language tool kit.

5) FEATURE EXTRACTION AND SIMILARITY CALCULATION
To extract the features for sentiment analysis, we used the Term Frequency – inverse document frequency. This technique is statistical and measures the relevancy of a word to a document. Thus, it multiplies two metrics, 1) the occurrence of a word in a document and 2) the inverse document frequency concerning a set of documents.

\[
\text{tf} - \text{idf}(t, d, D) = \text{tf}(t, d) \times \text{idf}(t, D)
\]  

Equation (1) is used for extracting the features. In this experiment top, 30% [5] of features were considered. Using this technique, Unigram, bigram, and trigram features were evaluated. To calculate the similarity between the features of citation sentences, Cosine similarity [40] was used. Cosine similarity can reflect the relatedness of a text corpus. The high value of cosine similarity, the higher the relatedness of input text.

6) MODEL SELECTION AND SCORE COMPUTATION
Different performance measures were used to evaluate the models, such as F-measure, Precision, Recall, and mean
accuracy values. For validation, we utilized the 10-fold technique. Six algorithms were investigated for sentiment analysis: Multinomial NB, Linear SVC, Bernoulli NB, Logistic Regression, and K-Neighbors. First, the model that produced high f-measure value than other models was selected. Furthermore, the linear Support Vector Classifier observed a high macro score compared to other models. Therefore, a linear support vector classifier was used to classify the citations into negative, positive, and neutral classes. The selected machine learning algorithm calculated the sentiment scores. The sentences were classified into three categories such as positive, negative, and neutral. The frequency of citations was also considered, and for each citation, the citation sentence was extracted, and we calculated the sentiment score.

G. CITATION COUNT
In this step, the frequency of the citations is calculated [41]. It is the identification of citation occurrences in a research document. For example, if a research article is cited five times in another article, the citation count would be 5. This experiment counts all the citation of citation pairs irrespective of their sections. For citation count calculation, ParCit [35] was used, which is an openly available tool. This tool considers the structure of the research article for citation extraction and calculation.

H. DOCUMENT SIMILARITY SCORE CALCULATION
The similarity of citation pairs such as cited and cited articles can be deemed important in verifying the important citation. To calculate the similarity, we considered the whole content of the research papers. For this purpose, the content was extracted from the files. Further, the preprocessing was performed for removing stop words were removed, and words were converted to their base by applying stemming. Further, the key terms were identified using cosine similarity and term frequency-inverse document frequency [40] on extracted vital terms. The similarity value indicated the relatedness of the research articles.

IV. RESULTS AND DISCUSSIONS
A. SECTION-WISE WEIGHT ESTIMATION
To conduct this research work, we utilized two datasets, D1 and D2. The dataset D1 was compiled by Valenzuela and two experts of the domain, who annotated this dataset. This dataset consisted of 457 citation pairs, out of which 388 citation pairs were non-important, and 69 citation pairs were annotated as important. We categorized these citations concerning their sections, and 155 citation pairs were observed in the Introduction section; similarly, 131 citations were in the Literature review, and 404 and 77 citations were found in the Methodology and Results and Discussion sections, respectively. Overall the citation found in dataset D1 was 767. The citations in the Methodology sections were more in number than in the other sections, and the minimum citations were in the Results and Discussion sections. For dataset D1, the characteristics are described in following Table 8.

While the dataset D2 consisted of 311 citation pairs but for ID’s 32, 71, 135, 152, 156, 157, 163, 164, 175, 180, 187, 191, 192, 195, 198, 199, 216, 222, 228, 230, 235, 244, 246, 246, 262, 266, 290, 303, 316, and 317, we were unable to download the articles. Therefore, we researched with 282 citation pairs, out of which 193 citation pairs were non-important, and 89 were important. Further, we considered the sections for citations; 157 citations were observed in Introduction, 122 citations in Literature Review, 116 were found in Methodology, and similarly, 69 citations were in the Results and Discussion sections of the citation pairs. The total citation frequency for all citation pairs was 464 because a citation can be made multiple times. The maximum citations were made in the Introduction sections, and the minimum ones were in the Results and Discussion sections. The statistics of dataset D2 are presented in following Table 9.

To automatically assign the weights to sections, we utilized two machine learning algorithms 1) Neural Network and Multiple Regression. However, both datasets were imbalanced as there were more non-important citations. Therefore, we applied Smote Filter while considering five neighboring instances. This filter creates virtual instances by considering the neighbor instances. These algorithms were trained on 60% data and tested on the remaining 40% [5].

In Multiple Regression, we kept the Y-intercept as 0, so there would be no need to add the constant value to the obtained weights. As a result, the obtained weights by both machine learning algorithms had a sum equal to 1. Table 10 presents the weights obtained by the Neural Network. The algorithm Neural Network assigned a maximum

| Total Citation Pairs | Important Citations Pairs | Non-Important Citations Pairs | Sections of Articles | Citations Frequency |
|----------------------|---------------------------|-------------------------------|----------------------|---------------------|
| D1                   | 69                        | 388                           | Introduction         | 135                 |
| Literature Review    | 131                       |                                |                      |                     |
| Methodology          | 404                       |                                |                      |                     |
| Results and Discussions | 77                       |                                |                      |                     |
| **Total**            | **531**                   | **160**                       |                      |                     |

| Total Citation Pairs | Important Citations Pairs | Non-Important Citations Pairs | Sections of Articles | Citations Frequency |
|----------------------|---------------------------|-------------------------------|----------------------|---------------------|
| D2                   | 89                        | 193                           | Introduction         | 157                 |
| Literature Review    | 122                       |                                |                      |                     |
| Methodology          | 116                       |                                |                      |                     |
| Results and Discussions | 69                       |                                |                      |                     |
| **Total**            | **282**                   | **199**                       |                      |                     |
TABLE 10. Section-wise weights by neural network.

| Algorithm       | Sections       | Assigned Weights | Order |
|-----------------|----------------|------------------|-------|
| Neural Network  | Introduction   | 0.19995378       | 3     |
|                 | Literature     | 0.28763501       | 2     |
|                 | Results and Discussion | 0.34514832   | 1     |

TABLE 11. Section-wise weights by multiple regression.

| Algorithm       | Sections       | Assigned Weights | Order |
|-----------------|----------------|------------------|-------|
| Multiple Regression | Introduction | 0.1891921316     | 3     |
|                 | Literature     | 0.1470393226     | 4     |
|                 | Methodology    | 0.3663496373     | 1     |
|                 | Results and Discussion | 0.2974189085 | 2     |

TABLE 12. Multiplication of weights with section-wise citation count.

| Paper   | Cited-by | Follow-up | Frequency | Introduction | Literature | Methodology | Results |
|---------|----------|-----------|-----------|--------------|------------|-------------|---------|
| A06-1043| C00-2140 | 0         | 1         | 0            | 0.19995378 | 0.28763501 | 0       |
| A06-1043| P02-1057 | 0         | 1         | 0            | 0.17626289 | 0           | 0       |
| H05-1079| D10-1074 | 0         | 1         | 0            | 0          | 0.34514832 | 0       |
| H05-1079| J07-3004 | 0         | 1         | 0            | 0          | 0           | 0       |
| H05-1079| N06-1009 | 1         | 4         | 0.76381512   | 0          | 0           | 0       |

weight to the Results and Discussion sections, and the least weight was assigned to the Literature Review sections. On the other hand, The Multiple Regression assigned more weight to the Methodology sections and less to the Results and Discussion sections, as mentioned in Table 11. At the same time, the research community focuses more on Results and Discussion citations. Therefore, we utilized the weights obtained by Neural Network for further manipulation. The weights were further multiplied to the section-wise in-text citations. For dataset D1, the multiplication of weights to the section-wise citation count is presented in Table 12.

B. SENTIMENT SCORE

To compute the sentiment score, we extracted the citation sentences and classified the sentences into positive, negative, and neutral categories. We considered six algorithms, such as Linear SVC, Multinomial NB, Bernoulli NB, K-Neighbors, and Logistic Regression, for extracting the essence of citations. These algorithms were trained on the separate training dataset, and we utilized Unigram, Bi-gram, and Tri-gram measures. These algorithms were evaluated based on Accuracy, Precision, Recall, and F-measure parameters. The following table presents the macro F-measure values with Unigram, Bi-gram, and Tri-gram features.

As described in Table 13, on average, the considered models produced better results with Unigram than Bigram and Trigram. Therefore, Unigram was selected for feature evaluation. The Weighted average, Micro average, and Macro average values for Accuracy, Precision, Recall, and F-measure are presented in the following Figure 3.

The overall results produced by Linear SVC were better than the other models. Therefore, for further computations, we utilized Linear SVC. This model was applied to citation sentences, and the sentences were categorized as positive, negative, and neutral sentences. The following table describes the results obtained with the Linear SVC algorithm.

In Table 14, we computed the sentiment of citation sentences concerning their number of occurrences. As in the first row, a paper is cited a single time and was classified as Neutral. While the last row explains that a paper was cited twice, and both times, it had different sentiments: one time it was positively cited, and one time it was cited as neutral.

C. CLASSIFICATION OF CITATIONS WITH ALL COMBINED FEATURES

To classify the citations, we combined all the considered features consisting of 1) Citation Count, 2) Content Similarity, 3) Section-wise in-text citation count, and 4) Citation Sentence Sentiment Score.

The Section-wise in-text citation count feature was further divided into four features such as 1) Introduction Citation Frequency, 2) Literature Review Frequency, 3) Methodology Citation Frequency, and 4) Results and Discussions Citation Frequency. Similarly, the Sentiment Scores were divided into three sub-features 1) Positive, 2) Negative, and 3) Neutral citation frequencies. Finally, we combined all these features and classified the citations using machine learning algorithms Support Vector Machine, Random Forest, and Multilayer
TABLE 13. Macro F-measure values.

| Features     | Linear SVC | Multinomial NB | Bernoulli NB | K-Neighbors | Logistic Regression |
|--------------|------------|----------------|--------------|-------------|---------------------|
| Unigram      | 0.43       | 0.31           | 0.31         | 0.35        | 0.37                |
| Bigram       | 0.42       | 0.31           | 0.40         | 0.36        | 0.36                |
| Trigram      | 0.41       | 0.32           | 0.39         | 0.35        | 0.36                |

TABLE 14. Sentiment of citation sentences.

| Paper   | Cited-by | Follow-up | Frequency | Positive Frequency | Negative Frequency | Neutral Frequency |
|---------|----------|-----------|-----------|--------------------|--------------------|-------------------|
| A00-1043| C00-2140 | 0         | 1         | 0                  | 0                  | 1                 |
| A00-1043| P02-1057 | 0         | 1         | 0                  | 0                  | 1                 |
| A97-1011| W09-1118 | 0         | 1         | 0                  | 0                  | 1                 |
| I03-2038| P06-4003 | 1         | 2         | 1                  | 0                  | 1                 |

Perceptron. We utilized Smote filter to balance important and non-important classes while considering five neighbors to create virtual instances. For dataset D1, the results are presented in Figure 4. The Random Forest produced better results than other models. This model achieved a 0.94 value for precision, 0.918 value for Recall, and 0.93 for F-measure. The highest accuracy achieved was 0.93, at the same time, the performance of other models, such as Multilayer Perceptrons and Support Vector Machine, was comparable. The values of F-measure and Accuracy achieved by both models were 0.84 and 0.85, respectively. At the same time, Multilayer Perceptron gained a 0.9 value of precision and a 0.79 value of Recall. SVM produced 0.88 precision and 0.814 Recall value.

While for dataset D2 Random Forest was observed with high results compared to other models. Random forest achieved 0.76 value of Precision, Recall, and F-measure. While Multilayer Perceptron gained 0.73 Precision, 0.84 Recall, and 0.497 F-measure. While SVM achieved 0.634 Precision value, 0.654 Recall value and 0.644 value of F-measure. While Random Forest achieved the maximum accuracy. The results of D2 are presented in Figure 5. On both datasets, the Random Forest model outperformed other candidate models. However, for dataset D1, the proposed approach achieved a value of precision of 0.94, and for D2, it was 0.76. There exists a difference in the results of D1 and D2. The reason for achieving higher results for D1 is that the articles in this dataset mostly contain multiple citations against a single article. Conversely, for D2, most articles contain single citations against a single article.

D. COMPARISON

Using dataset D1, the research work of Valenzuela et al. [7] achieved 0.68 precision values by utilizing metadata and content-based features. This work was further enhanced by Qayyum and Afzal et al. [10]. The author enhanced the precision value up to 0.72 by using metadata-based features only. Similar research was conducted by Aljuaid et al. [5], and the researcher achieved a 0.83 value of precision with the Random Forest algorithm. We have also contributed to important citation identification in our previous research work, and the precision value was enhanced to 0.85. Finally, the state-of-the-art approach of Wang et al. [12] further improved the results and gained a 0.91 precision value. The graphical comparison of different approaches till now is presented graphically in the following Figure 6.

While the dataset D2 was utilized by Faiza et al., Aljuaid et al., and in our previous research work. The research work of Faiza et al. gained a 0.62 F-measure, Aljuaid et al. achieved a 0.69 value F-measure, and in our previous contribution, we were able to enhance the value up to 0.72. In our proposed approach, we have added sentiment features that improved the results further. The comparison for dataset D2 is presented in Figure 7. The proposed approach utilized section-wise in-text citation weights, sentiment analysis,
and article similarity features which were not combinedly considered by any approach. Therefore this approach performed better than previous state-of-the-art approaches and achieved a higher F-measure value.

V. CONCLUSION

To conduct a research study, a citation is considered a scientific measure to evaluate the significance of the work. Citations are used for computing multiple aspects of research such as impact factor of journals, ranking of researchers, ranking of institutions, etc. While the criteria of computing these important measures, all the citations are counted with equal importance. The research community concluded that all citations are not equally important. The reasons for citations should be incorporated, as a citation providing background and the other one extending the work cannot be of the same worth. Therefore, researchers have developed different approaches to distinguish important citations from non-important citations. These state-of-the-art approaches are content-based, bibliographic based, or meta-data based. However, the achieved accuracy of these state-of-the-art approaches is insufficient for making potential decisions. In this work, we have introduced an approach based on four submodules such as 1) automatically assigning the appropriate weights to sections where the citations were made, using Neural Network, 2) sentiment analysis on citation sentences, 3) calculating the similarity of research articles, and 4) utilizing overall count of citations. We used two datasets, D1 and D2, collected by Valenzuela et al. and Faiza et al. to perform the citation classification. These were earlier used in state-of-the-art approaches. Multilayer Perceptron, Support Vector Machine, and Random Forest were utilized for classification. The Random Forest algorithm achieved the highest value. The results revealed that the proposed approach achieved a 0.94 value, comparatively higher than any other approach.

CONFLICT OF INTEREST

The authors have no conflict of interest to report regarding the present study.

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