Research Article

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To cite to this article: Akbay, T. (2022) Analysıs of Extended Realıty Publcatons in Informatıon Systems Research Area Through Text Mınıng and Natural Language Processıng Technıques. International Journal of Engineering and Innovative Research, 4(3), p216-228. DOI: 10.47933/ijeir.1190214

DOI: 10.47933/ijeir.1190214

To link to this artice: https://dergipark.org.tr/tr/pub/ijeir/archive

International Journal of Engineering and Innovative Research

http://dergipark.gov.tr/ijeir

ANALYSIS OF EXTENDED REALITY PUBLCATONS IN INFORMATION SYSTEMS RESEARCH AREA THROUGH TEXT MINING AND NATURAL LANGUAGE PROCESSING TECHNIQUES

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https://doi.org/10.47933/ijeir.1190214

(**Received:** 01.09.2022; **Accepted:** 01.10.2022)

ABSTRACT: The aim of the study is to cluster and to classify the scientific papers regarding Extended Reality indexed in Web of Science database. To achieve this goal, Extended Reality related publications were located and gathered from the database. NLTK library was used for tokenization, stop words removal, and lemmatization operations. The TF-IDF vectorizer method in the Sklearn library was used to convert words to vector format. Then, the keywords of the publications were clustered using K-Means. The keywords in each cluster were searched throughout the abstract of each publication. The publication was labeled as the name of the cluster wherein the largest number of keywords matches the words in its abstract. Then, Support Vector Classifier, and Multinomial Naïve Bayes machine learning algorithms and Gated Recurrent Unit deep learning algorithms were conducted for classification. The results of deep learning and machine learning have been compared and this comparison yielded that the dataset is more suitable for deep learning in comparison to machine learning. Accuracy values are reported as 90.4%, 77.2%, and 99.8% for Support Vector Classifier, Multinomial Naïve Bayes, and Gated Recurrent Unit respectively. This study provides evidence that the GRU architecture is more effective than the classical machine learning algorithms.

Keywords: extended reality; natural language processing, text mining, classification algorithms, gated recurrent unit, multinomial naïve bayes.

1. INTRODUCTION

Extended reality (XR) is one of the most epochal, advanced, and promising information technology which allows people to either experience the things that they have never done or do ordinary things more effectively and efficiently [1, 2]. The term Extended Reality covers both Augmented Reality (AR) and Virtual Reality (VR) while interchangeably used for Mixed Reality (MR) which is a combination AR and VR environments [3, 2]. Because the term Extended Reality covers other realities defined within the scope of Reality-Virtuality continuum [4] it is considered as an umbrella term for referring all immersive realities.

Milgram, Takemura, Utsumi and Kishino [5] proposed Reality and Virtuality as opposite ends of a *Reality-Virtuality (RV) continuum* and modeled as it appears in Figure-1 below.

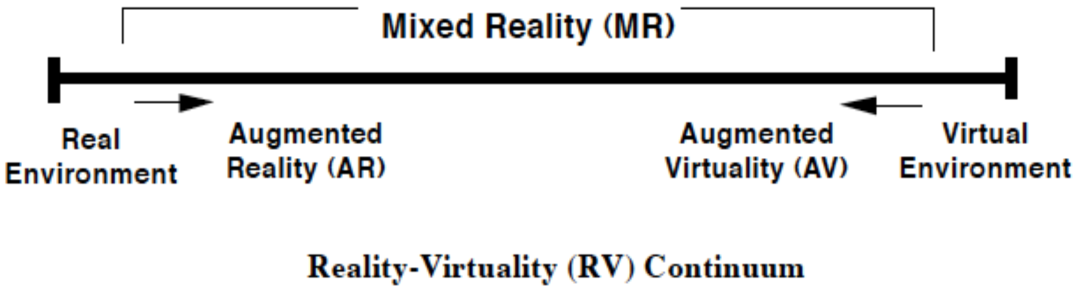

Figure 1. Reality-Virtuality continuum demonstration. Adapted from Milgram et al. [5].

In this Reality-Virtuality continuum, any point between the opposite ends represents what Milgram et al. [5] called a Mixed Reality (MR). There are two ideas embedded in this continuum: the first one is the real environment enhanced with virtual information which refers to Augmented Reality (AR), and the second one is the virtual environment having real object in it which refers to Augmented Virtuality (AV) [6].

In this continuum, moving toward real environment enhances reality, moving away from real environment enhances the virtuality and vice versa. Augmented Reality can be created by lengthening real world with computer-generated information (typically a graphical overlay) [7]. In the words of Szalavari, Schmalstieg, Fuhrmann and Gervautz [8], this design process "allows smooth extension of real objects with virtual properties in design processes" (p.40). Thus, as asserted by Kesim and Ozarslan [9], this process enables users to have intuitive and natural real-time experience. Alcaniz, Contero, Perez-Lopez, and Ortega [10] further claim that AR does not replace the reality but supplements contextual data into it for better understanding. From this point of view, AR can even go far beyond the reality and allow users to obtain more information than they can possibly gain through observation of the reality. Farkas [11] pointed out that AR superimposes content into the object you look at. Thus, Arvanitis et al., [12] argued that AR improves the users' perspective on understanding of complex concepts due to its ability of allowing users to view things in their natural environments.

Virtual Reality, on the other hand, defined by Steuer [13] as “a real or simulated environment in which a perceiver experiences telepresence” through a communication medium (p. 76). This is a broad definition which is not depending on any technological system or wearable device et al. There are numerous definitions in the literature to describe virtual reality concept yet, most of them relies on specific tool or feature (i.e., 3D Goggles) which makes those definitions meaningless once the technology in the definition changes. Unlike augmented reality, virtual reality immerses its users in virtual space and disengage them from the physical environment where they are in [14]. Virtual reality technologies allowed people to sense that they are a part of and present in another world which is apart from immediate physical reality [15]. Steffen et al., [14] pointed out two important advantages of virtual reality: (1) Exclusion from physical word allows physical representations to jump through space and time since physical laws exist only in physical reality, and (2) VR makes people experience things that are impossible in physical reality due to laws of nature such as breathing underwater and flying.

Numerous previously published studies regarding Extended Reality examine the XR related technologies and their effects in specific study domains (i.e., engineering, education, health care, marketing, manufacturing, entertainment) [14, 16]. At the time of conducting this research Web of Science core collection database yielded 65,998 and 28,986 hits for the search terms "virtual reality" and "augmented reality" respectively. Even though the most prestigious academic databases like Web of Science and SCOPUS offers categories for the publications, it would be beneficial to subcategorize or cluster the closely related publications together for readers and researchers. It would better to determining which cluster the manuscript, which will be published, belongs to through keywords. It helps researcher to locate the right journals whereas it helps editors to designate the reviewer who published research in the same topic coverage.

The aim of this research is to describe and to analyze the publications regarding Extended Reality in Information Systems area of research. In doing so, we hope to map and visualize publications regarding Extended Reality using machine learning clustering algorithm (i.e., K-Means). This research also aims to compare topic classification models created using machine and deep learning algorithms such as Linear Support Vector Classifier (SVC), Multinomial Naïve Bayes (MNB), and Gated Recurrent Unit (GRU). Therefore, the current study seeks answers for the following research questions:

1. In which areas are the extended reality studies in the field of information systems concentrated on?
2. Which algorithm among SVC, MNB, and GRU classifies an extended reality paper the most accurately?

2. METHOD

A systematic review method took place for the current study. During data gathering phase of the research, PRISMA [17] systematic review guideline was utilized to search the literature. Once all related publications are gathered, their keywords were clustered and then publications were classified using Naturel Language Processing (NLP) techniques to provide answers to the research question mentioned above using Python libraries.

K-Means clustering algorithm along with Term Frequency - Inverse Document Frequency (TF-IDF) word vectorization method was utilized for clustering author keywords gathered from the Web of Science (WoS) database. K-means is an unsupervised machine learning algorithm developed to classify a certain number of clusters over a given data set. It divides the data into k clusters according to their characteristics or properties [18]. Linear Support Vector Classifier (SVC), Multinomial Naïve Bayes (MNB), and Gated Recurrent Unit (GRU) algorithms were used for classifying all published works related to Extended Reality technology where they fall in the Information Systems research area in Web of Science Core Collection. SVC is a supervised learning machine technique that aims to find decision boundary relying on maximum distance between the boundary and the nearest training data points to the boundary of any class [19]. MNB classifier is a probabilistic learning technique, one of Bayesian models, which uses multinominal distribution while determining whether "inputted data belongs to a particular class by calculating posterior probabilities (p. 20) [20]. GRU can be considered as a simplified version of one of deep learning algorithm called Long-Short Term Memory (LSTM) [21] which is "is a subset of recurrent neural network (RNN) which is specifically used to train to learn long-term temporal dynamics with sequences of arbitrary length" (p. 1277) [22]. To check the accuracy of clustering conducted via K-Means clustering algorithm, co-word analysis also took place. Co-word analysis conducted through WoSviewer which is a bibliographic and scientific mapping tool [23].

After initial literature review on Extended Reality field, the following search query is used to locate all related studies published in the Computer Science Information Systems research category of Web of Science Core Collection database: TS=("immersive reality" OR "virtual reality" OR "augmented reality" OR "mixed reality" OR "extended reality") and Article (Document Types) and Computer Science Information Systems (Web of Science Categories) and Computer Science (Research Areas) and English (Languages). The search is also covered only the studies that were published within the last five years. In this query the abbreviation TS stands for 'Topic' in Web of Science database which covers the following fields: Title, Abstract, Author Keywords, and Keywords Plus. Thus, the keywords written in the query are searched throughout those fields and then, the publications possessing any of the search words in the query are extracted from Web of Science database for further analysis.

Through this search strategy it has been aimed to gain the data regarding followings: title of the publication, author info, date of publication, abstract, author keywords, publisher, and citation info.

Through this search, the publications are omitted from the current study if they are

- published more than five years ago
- written in a language other than English
- comments/editorial etc.
- not relevant to Extended Reality

After removal of those publications did not meet the exclusion criteria, I processed to analysis with 1,882 publications.

3. ANALYSIS

Data analyzed through Natural Language Processing (NLP) technique after data cleaning and pre-processing procedure. During data pre-processing via Natural Language Toolkit (NLTK) package in Python, text in the document goes through the following steps: extraction, cleaning up, parsing the content, retrieval, consolidation, conversion into corpus data, and noise (punctuations, numbers, spaces etc.) cleaning. Deficiencies, incorrect data, and outliers in our dataset adversely affect the performance of our classification model. For this reason, it is necessary to apply various preprocessing steps on our data. The main purpose of the preprocessing stage is to determine the stem of the words by purifying the data from punctuation marks, affixes, and conjunctions and prepositions. It is aimed to give the determined word root groups to the classification model in a way that does not disturb the semantic integrity of the sentence. Therefore, tokenization, stop words removal, and lemmatization operations are performed, and words are converted into vectors applying the TF-IDF method. TF-IDF value is a statistical value that describes the relationship between the word and the document in which it is located.

In our study, NLTK library was used for tokenization, stop words removal, and lemmatization operations. The Term Frequency–Inverse Document Frequency (TF-IDF) vectorizer (i.e., Equation 1) method in the Sklearn library was used to convert words to vector format.

$$w_{x,y} = tf_{x,y} \ x \ \log(\frac{N}{df_x}) \ (Equation\ 1)$$

$tf_{x,y}$ = frequency of x in y

df_x = number of documents containing x

N = total number of documents

The TF-IDF method calculates the Term Frequency and Inverse Document Frequency values. Term Frequency is a value that shows the frequency of the word in the text. Inverse Document Frequency, on the other hand, looks at how important the word is to the text.

After standard data pre-processing procedures using NLTK package in Python, NLP algorithm converts corpus into structured data to fulfill word segmentation which is crucial to text mining. K-means clustering algorithm and TF-IDF word vectorization method were used together for text (i.e., author keywords) categorization. After the preprocessing steps of the author keywords and abstracts came from the Web of Science database, they were converted into vectors applying TF-IDF. K-Means clustering algorithm is used to extract meaningful results from vector data and to perform labeling. The K-Means clustering algorithm is preferred because it can be scaled to large data sets, easy to adapt to new samples, generalizes different cluster types and guarantees unification. Grid-search method was used to find the best number of clusters in the K-Means algorithm. The data were divided into categories by choosing the number of clusters with the highest score.

The results (i.e., author keywords in each cluster) obtained from the clustering algorithm were revisited and revised by domain experts (i.e., computer engineering faculty members). The data set passed through preprocessing and labeling procedures were divided into training and test datasets for the classification algorithm. In the current study, classification was made using Linear Support Vector Classifier, Multinomial Naïve Bayes and Gated Recurrent Unit (GRU) methods. Each algorithm applied to the data has achieved the desired results with high performance.

4. RESULTS

After the preprocessing phase is completed, using the Elbow Method with K-Means clustering algorithm, clustering procedure is done with the most appropriate k number for our data. Clustering performed on most frequent (frequency≥5) keywords dataset. Using the K-means++ initializer hyperparameter, 10000 iterations of training are performed. Within the scope of clustering, our dataset is divided into five clusters. The keywords in each cluster are revisited and revised by two domain experts (i.e., academic staff at computer engineering department). Domain experts suggested to remove some keywords and subdivide some clusters. Based upon their suggestions, final clustering yield seven clusters. Domain experts titled those cluster as follows:

Cluster 0: Solid & 3D Modeling (23 keywords)

Cluster 1: Cloud & Edge Computing (32 keywords)

Cluster 2: Machine & Deep Learning (59 keywords)

Cluster 3: User & Quality Experience (53 keywords)

Cluster 4: 3D Display & Visualization (60 keywords)

Cluster 5: IoT & Wireless Sensor Network (92 keywords)

Cluster 6: Education & Educational Games (46 keywords)

Co-word analysis conducted through WoSviewer. The co-word analysis map below also yielded seven clusters. Yet, it is a bit different than our classification since the logics behind the two categorizations are totally different. Nonetheless, it provides insighted domain experts while they revise keyword clusters yielded by k-Means clustering.

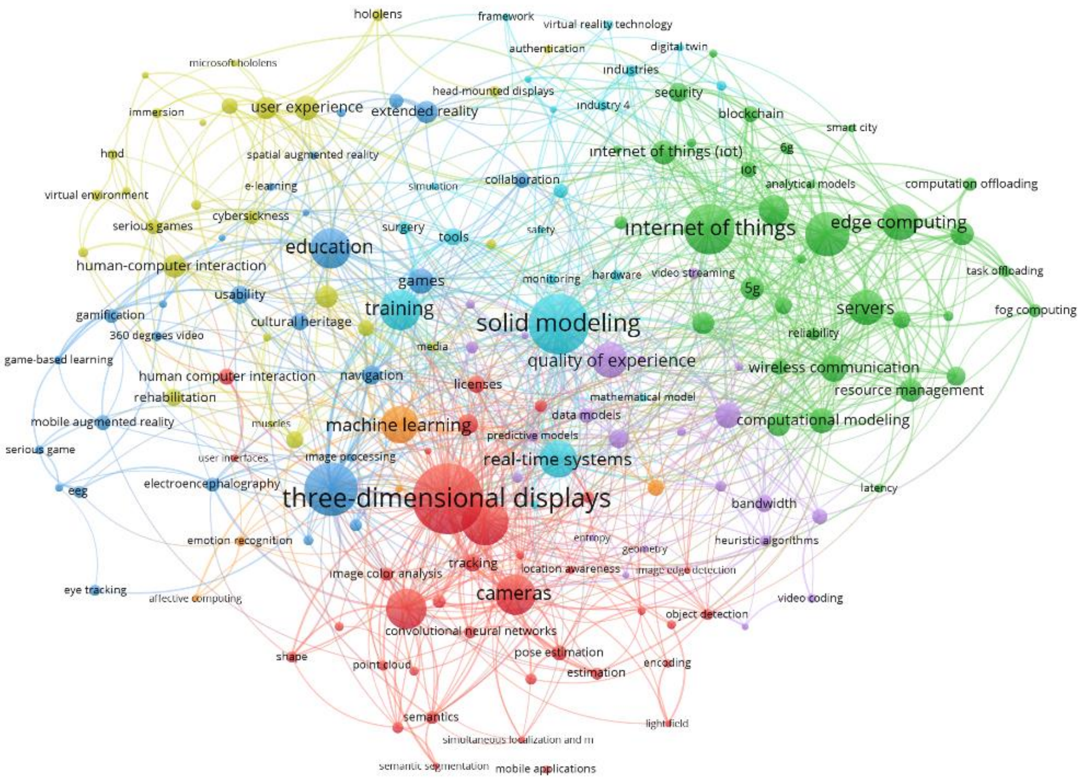

Figure 2. Co-word analysis map.

The keywords in each cluster were searched on the article abstracts in the dataset. Each article was labeled to the cluster where the keyword search within the abstract data yields the highest number of keywords. For instance, the results of keyword search in the sample abstract given Table-1 below.

Table 1. Labeling sample.

Cluster Names	Solid & 3D Modeling	Cloud & Edge Computing	Machine & Deep Learning	User & Quality Experience	3D Display & Visualization	IoT & Wireless Sensor Network	Education & Educational
Number of Keyword Hit in during the Search	2	0	0	11	5	2	2
				Max value			

Viewing table, it is evident that the abstract, wherein the keyword search is performed, possess the highest number of keywords from the cluster titled “User & Quality Experience”. Therefore, the article in this sample is labeled to *User & Quality Experience* cluster. Thus, 1,882 article is automatically labeled to the cluster where the highest number of search term (i.e., keywords in the clusters) found. The distribution of the articles is provided in Table-2 below.

Table 2. Distribution of articles among the clusters.

Cluster Name	Number of articles fall into
Cloud & Edge Computing	69
IoT & Wireless Sensor Network	308
Solid & 3D Modeling	18
User & Quality Experience	119
Education & Educational Games	493
Machine & Deep Learning	368
3D Display & Visualization	480

27 articles are not being labeled since their abstract search was unable yield any value for nay cluster. These 27 data removed from dataset before running classification algorithms.

4.1.Classification Results

After the automatic labeling process, tokenization, remove stop words, lemmatization and vectorize processes were applied within the scope of NLP preprocessing steps using 1882 article abstracts. These steps were performed using the NLTK and TFIDF libraries. Articles that do not receive any value (i.e., number of keywords from each cluster) could not be labeled, therefore they were removed from the dataset before conducting classification. Since the dataset imbalanced, which means that unequal distribution of the clusters in the dataset, minority sampling strategy in ADASYN (Adaptive Synthetic) algorithm. Basic principle behind the ADASYN is adaptively (i.e., without copying the same minority data) generating minority data samples to make dataset more balanced [24]. Thus, it is aimed to obtain higher performance in the classification algorithms. Our data obtained with ADASYN is divided as 80% training and 20% test dataset.

In the current study, Support Vector Classifier (SVC), and Multinomial Naïve Bayes (MNB) machine learning algorithms and Gated Recurrent Unit (GRU) deep learning algorithms were conducted. The results of deep learning and machine learning have been compared and this comparison yielded that the dataset is more suitable for deep learning in comparison to machine learning. Accuracy values are reported as 90.4%, 77.2%, and 99.8% for SVC, MNB, and GRU respectively. This study provides evidence that the GRU architecture is more effective than the classical machine learning algorithms.

As a result of the training with SVC, 90.4% accuracy values were achieved. Table-3 below shows the confusion matrix.

Table 3. SVC confusion matrix.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
172	0	17	3	8	0	1
0	**19**	0	3	0	0	0
2	2	**136**	0	2	0	2
0	0	5	**113**	0	0	0
7	1	7	6	**105**	2	1

0	0	0	0	0	**159**	0
3	0	3	2	0	0	**25**

The precision, recall and f1-score values of the SVC algorithm based on the results obtained from the Confusion Matrix are presented in the Table-4 below.

Table 4. SVC classification report.

		Precision	Recall	f-1 Score
Clusters	Cloud & Edge Computing	0.93	0.86	0.89
	IoT & Wireless Sensor Network	0.86	0.86	0.86
	Solid & 3D Modeling	0.81	0.94	0.87
	User & Quality Experience	0.89	0.96	0.92
	Education & Educational Games	0.91	0.81	0.86
	Machine & Deep Learning	0.99	1.00	0.99
	3D Display & Visualization	0.86	0.76	0.81
Accuracy				0.90
Macro avg		0.89	0.88	0.89
Weighted avg		0.91	0.90	0.90

As a result of the training with MNB, 77.2% accuracy values were achieved. Table-5 below shows the confusion matrix.

Table 5. MNB confusion matrix.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
155	0	39	1	0	6	0
7	**0**	0	8	6	1	0
9	0	**120**	3	9	3	0
14	0	21	**71**	10	2	0
10	0	38	1	**77**	3	0
0	0	0	0	0	**159**	0
8	0	22	1	1	1	**0**

The precision, recall and f1-score values of the MNB algorithm based on the results obtained from the Confusion Matrix are presented in the Table-6 below.

Table 6. SVC classification report.

		Precision	Recall	f-1 Score
Clusters	Cloud & Edge Computing	0.76	0.77	0.77
	IoT & Wireless Sensor Network	0.00	0.00	0.00
	Solid & 3D Modeling	0.50	0.83	0.62
	User & Quality Experience	0.84	0.60	0.70
	Education & Educational Games	0.75	0.60	0.66
	Machine & Deep Learning	0.91	1.00	0.95
	3D Display & Visualization	0.00	0.00	0.00
Accuracy				0.72
Macro avg		0.54	0.54	0.53
Weighted avg		0.70	0.72	0.70

For deep learning, three-layer GRU model consisting of 16, 8, and 4 units was used.

The GRU model was run in 60 different configurations using various embedding size, batch size and epoch size grid-search. Accuracy results of the grid-searches were reported in Table-7 below.

Table 7. Accuracy results of grid-search algorithm on GRU architecture.

Batch Size		4			8			16			32		
Epoch Size		10	30	50	10	30	50	10	30	50	10	30	50
Embedding Size	10	0.967	0.993	0.998	0.825	0.989	0.995	0.914	0.921	0.990	0.673	0.942	0.998
	20	0.780	0.998	0.996	0.503	0.986	0.995	0.972	0.891	0.989	0.726	0.950	0.990
	30	0.910	0.996	0.998	0.979	0.986	0.961	0.913	0.969	0.984	0.913	0.989	0.958
	40	0.910	0.986	**0.998**	0.913	0.993	0.992	0.913	0.976	0.992	0.851	0.942	0.955
	50	0.961	0.996	0.995	0.965	0.989	0.996	0.652	0.961	0.986	0.709	0.979	0.993

By using the GRU architecture, maximum 99.84% accuracy and minimum 1.80% loss values were achieved because of the training the model with the following parameters: [Epoch Count: 50, Batch Size: 4, Embedding Size: 40]. Table-8 below presents the confusion matrix regarding this training.

Table 8. GRU confusion matrix.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
201	0	0	0	0	0	0
0	**22**	0	0	0	0	0
0	0	**144**	0	0	0	0
0	0	0	**118**	0	0	0
0	0	0	0	**129**	0	0
0	0	0	0	0	**158**	**1**
0	0	0	0	0	0	**33**

Precision, recall and f1-score values are obtained via the results of Confusion Matrix. GRU The classification report is presented in Table-9 below.

Table 9. GRU classification report.

		Precision	Recall	f-1 Score
Clusters	Cloud & Edge Computing	1.00	1.00	1.00
	IoT & Wireless Sensor Network	1.00	1.00	1.00
	Solid & 3D Modeling	1.00	1.00	1.00
	User & Quality Experience	1.00	1.00	1.00
	Education & Educational Games	1.00	0.99	1.00
	Machine & Deep Learning	0.97	1.00	0.99
	3D Display & Visualization	1.00	1.00	1.00
Accuracy				1.00
Macro avg		1.00	1.00	1.00
Weighted avg		1.00	1.00	1.00

Training accuracy and loss graphs of the GRU architecture are given in Figure 3 below.

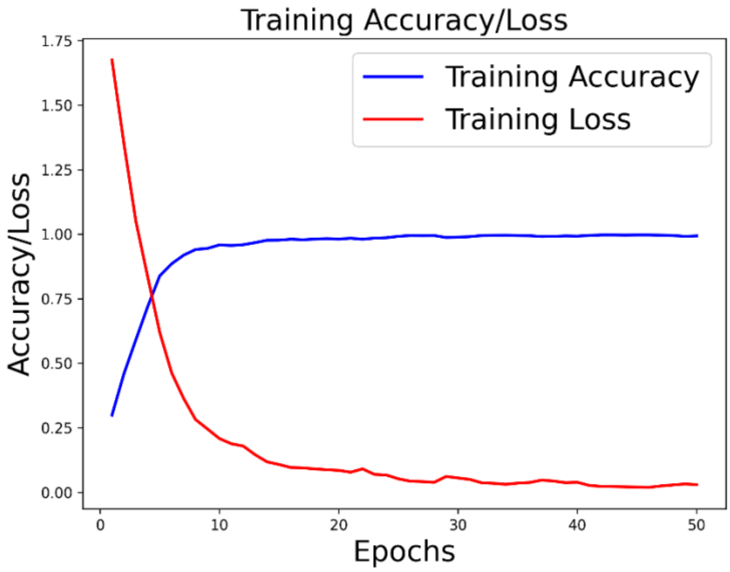

Figure 3. Training Accuracy/Loss Graph.

The accuracy, mean absolute error, mean square error and r^2 score results of SVC, MNB and GRU algorithms are shown in Table-10 below.

Table 10. The Accuracy, Mean Absolute Error, Mean Square Error, and R^2 Scores.

	Accuracy	Mean Absolute Error	Mean Square Error	R^2 Score
SVC	0.904	0.249	0.820	0.781
MNB	0.722	0.673	2.060	0.451
GRU	0.998	0.004	0.014	0.995

It can be concluded that GRU model is more appropriate for classifying publications based upon their keyword.

4.2. Discussion and Conclusion

The study findings showed that most of the Extended Reality related articles have been published for the last five years focused on education and educational games. The total published Extended Reality related articles focus on education and educational games, according to the study finding, is 493. The number of articles focused on 3D display and visualization in extended reality found to be as 480. Machine learning and deep learning is the third subject that most articles focus on. The number of articles focused on this topic are 368. The number of articles focusing on other areas are listed as follows: 308 articles were labeled as internet of things and wireless sensor network related publication, 119 articles were labeled as user and quality experience related publication, 69 articles were labeled as cloud and edge computing related article, and lastly 18 articles were labeled as solid and 3D modeling related article. I am not surprised by the number of articles published in the education and educational games focused Extended Reality papers even though Web of Science category where all those education and educational games related articles published surprised me.

The largest cluster is found to be as Education and Educational Games. It is understandable why XR technologies studied in education area the most because of the benefits of the technology to the education field. Some benefits of extended reality environments in education and training are listed below:

- students easily understand the objects that are manipulated within the virtual environment [25].
- These technologies enable students to learn subjects beyond class boundaries and pre-defined time interval [26].
- These technologies allow users to turn abstract concepts into mode concrete ones to enhance students' understandings on those concepts [27].
- Through these technologies, learning experience become more interactive and engaging [27].
- These technologies increase students' motivation and attract their attention [28].
- These technologies enable students to observe and experience teaching subjects that nearly impossible to observe or dangerous to experience otherwise [29].

In addition to the list above, during the covid-19 pandemic lockdown encouraged educational institutions for online learning in virtual environments. Since the current study analyzed the papers have been published in last five years, the pandemic must have played an important role over the distribution of published articles.

Second cluster having the most articles published is 3D Display and Visualization. Emergence of this topic among the articles regarding extended reality may be expected since some 3D display technologies (i.e., Virtual Reality) can completely immerse users in 3D worlds while some display technologies (i.e., Augmented Reality) project 3D objects into the user's physical environment [32]. It is acknowledgeable that 480 articles among published ones 1882 focus on 3D display features of extended reality technologies.

Third largest cluster is Machine and Deep Learning. Extended reality and machine learning are two distinct study areas, and their applications and focuses are different. Extended reality tries to extend people's capacities and experiences through computer generated environments whereas machine and deep learning are involved in information processing through the way of replication humans [30]. However, combination of those study areas generates new opportunities. Extended reality serves artificial intelligence systems When the literature is examined, it is seen that sometimes extended reality technologies serve for artificial intelligence systems and sometimes artificial intelligence technologies serve for extended reality systems. Extended reality applications can become more useful and valuable through artificial intelligence because it makes communication easier by facilitating XR software to track things like gestures and eye movements, thus XR environment become more immerse as well as it makes [30, 31]. In other respects, extended reality helps artificial intelligence systems by (1) facilitating their performance (2) training machine/ deep learning data without data comes from physical world, (3) simulate novel cases for training [30].

Three different classification algorithms with different parameters have been executed to determine the classification model suits the data most. Two of them are machine learning classification algorithms (i.e., SVC and MNB) whereas one of them was deep learning algorithm (i.e., GRU). The model that provides the most accurate classification result was GRU deep learning algorithm which classifies the dataset with 99.8% accuracy. This classification model may be used for assessing the scope of any extended reality manuscript which may be valuable while selecting a journal since all articles are being labeled to one of cluster, and assigning a reviewer based on the focus of the manuscript.

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