Multimodal Data Analysis and Machine Learning Techniques: A Comparison and Review

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ABSTRACT

In the last few years, data analytics and machine learning have made immense progress in terms of technological advancements. It has become possible for machines and computers to have the ability to understand, recognize, and analyze emotions. We know that the affective reactions Fusion supports different methods in sentiment analysis research that uses audio, video, and text to predict fundamental emotions (anger, joy, sorrow, antipathy, fear, and surprise) researchers from different fields and disciplines are focused on emotional recognition. Multimodal analysis is always challenging for both devices and researchers. The MSA (multimodal sentiment analysis) is one of the studies in favor of multiple sclerosis. This research briefly describes several of the recently proposed methods and MSA applications. The main goal of this study is to give a comprehensive overview of the potential issues related to MSAs and other related topics. This activity helps to explore emotions, attitudes, and opinions. However, for multimodal sentiment analysis, we are particularly concerned with various modes of input where information is available in three modalities: Audio, video, and text

Keywords: Emotion recognition, effective computing, Data analytics, Machine learning, Multimodality.

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1. INTRODUCTION

Human behavior is incredibly influenced by abstract emotions and beliefs. Because the transmission of other people's evaluations is programmed into each individual's brain and represents us as social beings, the decisions we make are heavily influenced by the impression others have of the world. According to social cognitive theory, learning is a functioning valuable cycle where individuals effectively search out and handle data (Bandura 2001; Pintrich 2000). Define learning as the relationship of affective processes within its cognitive learning context(Zimmermann and Schunk ;2011) . Learners are responsible not only on behalf of their own cognitions, motivations and emotions, but also for the cognitions, emotions and actions of others. Opinion extraction and its mining is an additional name for sentiment data analysis and falls into the categories for machine-learning and data analysis. The applications of various techniques are used in social media, opinion mining, and sentiment analysis in personal or industrial use data of analysis.

A large amount of information regarding various individual entities are captured in digital form everyday to determine a particular estimation of mood is typically either positive or a negative. It is important to seek the input of others when it is necessary to draw conclusions or final results. Sentiment analysis involves classifying data into different classes, such as optimistic, reasonable, unreasonable, negative or neutral, Ineffective.

In the area of encouragement and challenge, recent work has been done on implementing opinion mining that caters to individual needs. Sentiment analysis requires a good training set and a good dataset for accuracy. Understanding these processes, as well as developing efficient and effective methodologies for enabling successful learning, pose significant challenges for learning science. Methodology for exploring

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the complexities of active learning, including cognitive, behavioral, and affective processes, as well as the influence of peers and technical assistance, is to take a multimodal perspective.

Data collection

This work uses modes to collect data about themes and then draws conclusions or estimates about those themes. Some sites provide an API (Application Programming Interface), which makes it easy to set up an automatic way of accessing the site These processes, as well as the development of efficient and effective methodologies for enabling successful learning, One methodology for exploring the complexities of active learning,

Classification

Support Vector Machine (SVM)-Naive Bayes (NB)-Decision trees, and Neural Networks are only a few of the methods used in the current work being done. A training set is provided to the corpus for learning, followed by accuracy of multiple classifiers on the test set compared to one another.

Machine Learning Techniques used in Data Analytic

Most machine learning algorithms can be put into one of four groups, as shown in Fig.1 by Mohammed M., Khan M_B., et al. (2016). Here's a quick look at each associated learning technique and how it can be used to resolve problems in an authentic way.

Supervised : here supervised learning, a machine learns a capability that maps a contribution to yield by seeing example input-yield matches (Han J et al 2011). It learns a capability by checking out at named preparing information and a bunch of preparing models. (Sarker IH et al., 2020) An errand-driven approach is utilized to do regulated realization when clear objectives are set to be reached from a specific arrangement of information sources. "Characterization," which sorts the measurements into gatherings. These are the most well-known managed assignments, as indicated by the insights. Text classification, a type of managed learning, is one strategy for figuring out what a piece of text, for example, a tweet or an item survey, or others.

Unsupervised: Unsupervised learning is an information-driven strategy that looks at unlabeled datasets without the help of a human. (Han J et al 2011). This is utilized a great deal to get generative elements, find significant patterns and designs, bunch results, and accomplish exploratory work. Grouping, thickness assessment, highlight learning, dimensionality decrease, finding affiliation rules, tracking down anomalies, and so on.

Semi-supervised: A Semi-supervise learning model's definitive goal is to empower better redactions. then the model could do with simply the named information. Semi-supervise learning is utilized for different errands, including text characterization, misrepresentation identification, information naming, and machine interpretation.

The above-examined regulated and unaided procedures are joined in Semi-supervise learning. It is material for both distinct and unlabeled information. (Sarker IH et al 2020). The framework has gotten the hang of involving a mix of marked and unlabeled information in this method of learning. In this way, in reality, named information might be not many and unlabeled information might be a large number. This is where semi-directed learning proves to be useful (Mohammed M, Khan MB.et al 2016).

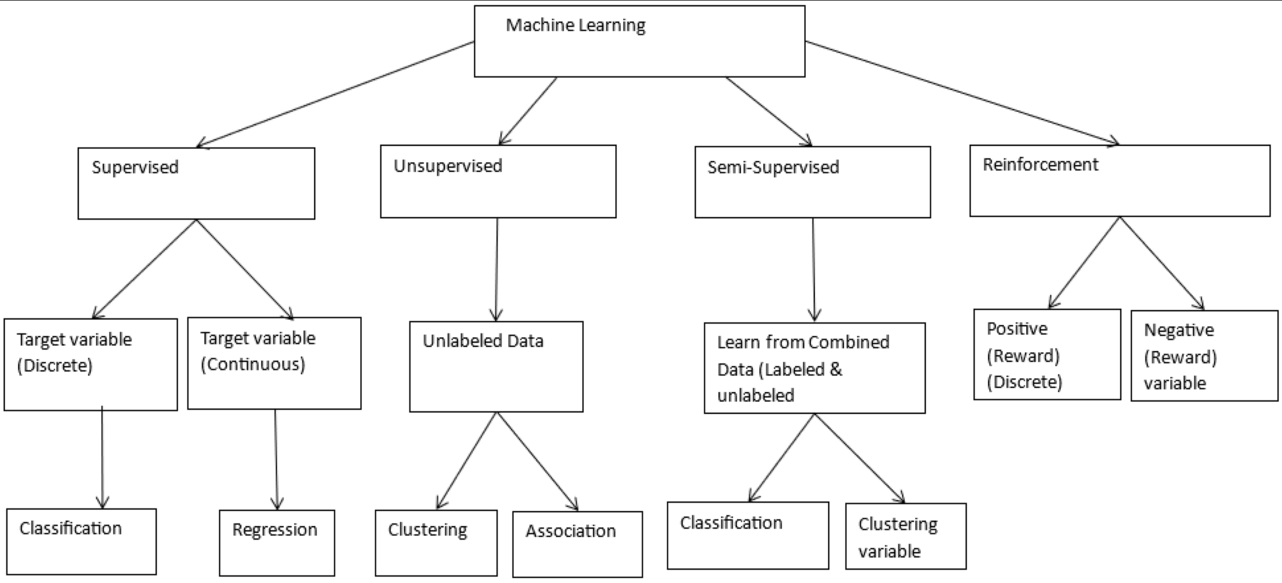

Figure 1: Various machine learning techniques and its type.

- **Reinforcement**: Reinforcement learning is a kind of ML algorithm that allows the software program to act as actor agents and build machines to sort out the most ideal method for acting in a specific circumstance or climate consequently. This is additionally called a climate-driven approach. the ultimate objective is to utilize everything climate says to us to make strides that will improve the prize or diminish the chance of hazard (Mohammed M, Khan MB.et al 2016)

In Table 1, We give an outline of a few ML strategies utilizing substantial models. We can exhibit an exhaustive comprehension of AI strategies in this, empowering us to work on the presentation of information-driven applications.

Table 1: Examples of several machine learning and it's approaches

Model building	Used in	Learning type	Examples
From labeled data, algorithms or models can learn.	Task Driven Methodology	Supervised	- Regression - Classification
Algorithm(s) or model(s) acquire knowledge from unlabeled data.	Application Driven by data	Unsupervised	–Associations-Clustering - Reduction of Dimensionality
Models are developed by combining data.	Labels & Unlabeled Data	Semi-supervised	Clustering -Classification
Models are constructed taking place either compensation or a liability.	An environmentally conscious approach	Reinforcement	Classification, control

2. TASKS AND ALGORITHMS FOR MACHINE LEARNING

We explore several machine learning algorithms, including characteristic engineering for dimensionality-reduction, association-rule and its learning, data clustering, regression, classification, and deep learning techniques. Figure 2 demonstrates the overall layout of machine-learning-based analytical representation. Phase 1 aims to train the model with past data, and in Phase 2, is to train and test the model

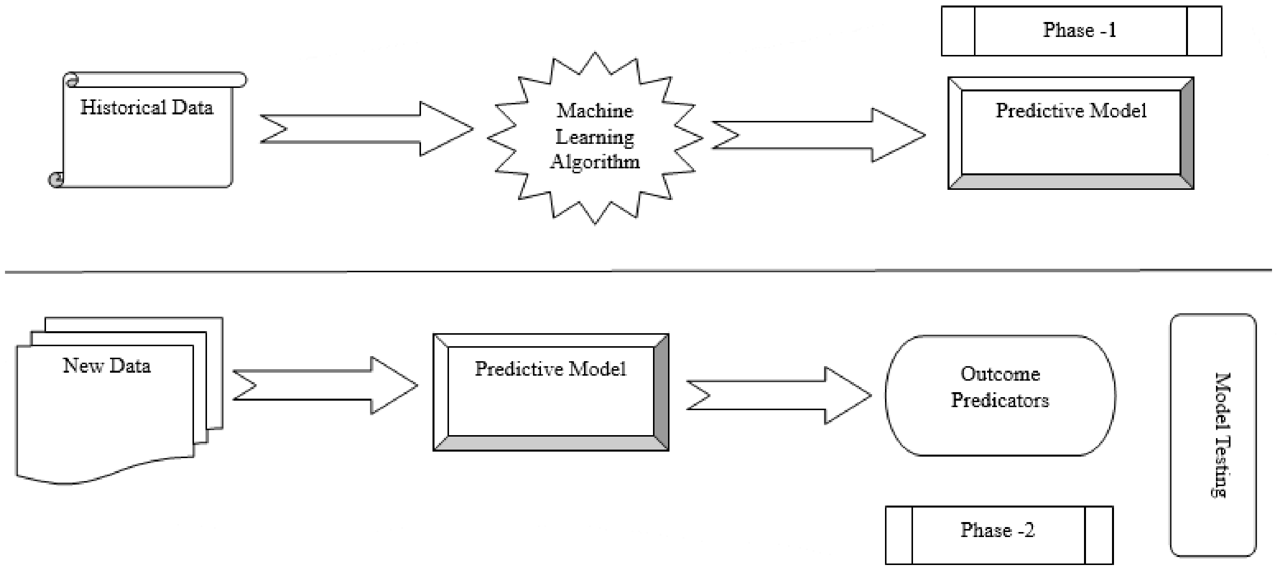

Figure 2: A schematic diagram of a prediction system based on machine learning that takes both the testing and training phases.

2.1 Classification analysis

In machine learning, it is a classification form of learning in a supervised manner. It is furthermore a problem with predictive modeling when a social class description for a given case is projected (Han J et al 2011). The capability (f) from input factors (A) to yield factors (B) as a target, and name, is characterized numerically by the accompanying conditions:

$$b = x + ya + e \quad (1)$$

$$b = x + y_1a_1 + y_2a_2 + \ldots\ldots\ldots + y_na_n + e \quad (2)$$

Wherever a represents the expropriate and block, y is the outline slope, and e the error period Based on the predictor variable, this equation can be used to predict the value of the goal variable (s). It may be used to bet the class of hard and fast statistics factors in both structured and unstructured records.

***Binary classification** is a way of sorting things into two groups, like "true" and "false" or "yes" and "no". In these types of tasks, one category could be the regular state and another class could be the abnormal state. (Han J. et al., 2011).

***Multiclass classification:** Typically, this is used to describe activities with two additional class labels. Multi-class classification tasks do not include ordinary and anomalous outcomes, In contrast to binary classifiers, we classify instances into one of several pre-established classes. (Han J. et al., 2011).

***Multi-label classification:** When an example is connected to more than one class or label, it's crucial to consider multi-label classification, and we are aware that many classification algorithms have been suggested in the disciplines of ML and data science [Han J et al., 2011, Frank et al., 2005]. It is therefore a more thorough type of multiclass categorization in which the problems and classes are grouped hierarchically, with each example being able to relate to more than one class at each level of the hierarchy.

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3 LITERATURE SURVEY

We present an outline of multimodal concentrations on learning and its fundamental processes as a study to work out how to utilize and link information modalities while exploring different components of learning processes. We scrutinize the journal, country, and subject to cover its attributes. We also investigate the information methodology, the exploration technique, the kind of learning, and the modalities used to concentrate on the different foci. We organize, assess, and decode different arrangements of information modalities to utilize pairs to evaluate numerous components of cognitive, credible, and profound learning to encounter a solution to the accompanying exploration question:

RQ1: What and how are the following difficulties addressed to indicate the data mult-modalities in use to restrict cognitive, motivational, and influencing basic cognitive processes involved in online and other reviews, according to research published?

RQ2: What are the current states of the journal's intended audience and the region of the investigation into learning processes using data-modal research?

RQ3: Which tasks are resolved by machine learning algorithms to mine opinions and do sentimental/emotional analysis?

4 CHALLENGES IN RESEARCH DIRECTIONS

Our research has various subjects in the space of machine learning algorithms for keen information examination and applications. In this part, we talk about framing the difficulties we've experienced, as well as potential review possibilities and future headings. More often than not, the nature and characteristics of the information, as well as how really the learning calculations perform, characterize how fruitful and effective an AI arrangement is "Uses of ML" shows that it isn't difficult to gather information in regions like network safety, Part, medical care, farming, and conduct examination, despite the fact that the internet today makes it conceivable to create immense measures of information regularly. Thus, there is helpful information for the applications that utilize AI. Thus, at what time is functional in reality information, it is vital to study how information is gathered. The AI calculations examined in the "Machine Learning Tasks and Algorithms" segment have a major result on the class of the information, its amount is accessible for preparation, and the model that is made as a result.

5 OVERVIEW OF STUDY

After applying the systematic research publications reviews Table 2 offers a comprehensive list of publications grouped by author(s), target journal, country of study, covered subject, participant characteristics, educational level, focus, kind of

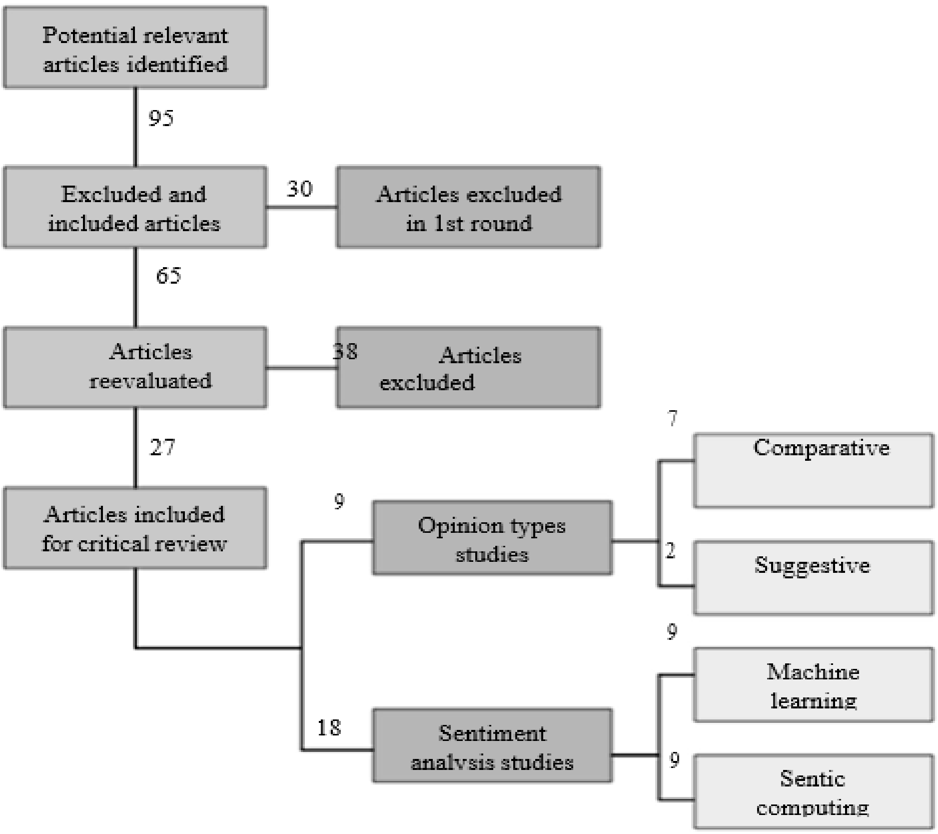

Figure 3: A progression of the learning and selection of articles

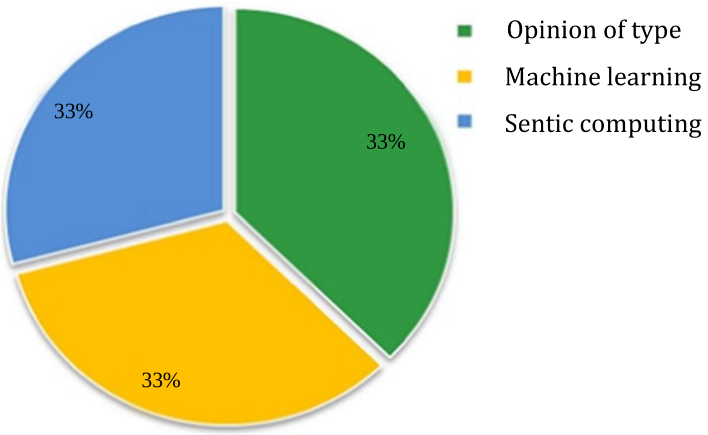

Figure 4: classification of fundamental study for review

data modality, research technique, learning type, learning context, and modality-focus. Figure 3 presents the phases of the review choice cycle that was embraced for the efficient audit introduced in this paper. Figure 4 demonstrates that 33% respect audit types. Concerning SA strategies, 33% utilize ML(Machine Learning) procedures and 33% Sentic processing methods. The distribution of assessed papers is from (2002 to 2019). These studies focus on the general evaluation of opinion and its types (9 out of 27), on the S.A task utilizing M.L(9 out of 27), and on Sentic computation (9 out of 27). These investigations are assessed utilizing accuracy, precision and F-measure.

5.1 Results for research question:1

More than 95 multimodal papers were found after searching the journals System (9 cases), Recall (7 cases), English Language Teaching (6 cases), BMC Medical Education (6 cases), and Human Behavior and Computers (6 cases) (five). The remainder was made up of publications in the social sciences and humanities, such as Teaching and Teacher Education, and foreign journals, such as the Journal of Research in Education. Most multimodal research studies employed mixed methodologies to investigate various components of cognitive, motivational, and emotional learning processes. According to the study, the majority of research has focused on how people learn alone, followed by how people learn in pairs, trios, small groups, and big groups. In 50 of the experiments, only numbers were used (e.g., student products, surveys, and performance tests).

5.2 Results for research question:2

More than 38 publications only emphasized the cognitive aspects of studying, and 17 articles only mentioned motivation. There have been seven writings on self-studying that are typically selective in terms of what cognitive and emotional aspects are covered. Over 95 publications have focused on the motivational and cognitive foundations of learning. The finest 27 studies examined both the emotional and sentimental components, and 9 articles were gathered on the combination of cognitive, emotional, and motivational learning facts. The most fascinating aspect of all learning, both in individual and group contexts, is cognition, whereas conjecture is the least certain. When we used the publications that were studied in the mixed learning environment, there was no clear sample is found:

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Table 2: Summary of the respective modality, its Type and focus in the reviewed publication

S.no	Journal	Reference	Modality (- > focus)	T y p e (Modality)	Country (conducted study)	Focus (1:Cognition, 2:Emotion, 3:Motivation)	Learning Type(1:Individual , 2:Collaborative 3: Mixed)	Method(1:Qualitative, 2:Quantitative 3:Mixed)
1	Eur. J. Dent. Educ.	Bowman (2017)	10- > 2, 12- > 1,2	10, 12	UK	1, 2	1	2
2	Educational Technology & Society	De Witt et al. (2017)	9- > 1, 10- > 1, 17- > 1	9, 10, 17	Malaysia	1	2	1
3	Research in Science Education	Eastwood et al. (2013)	1- > 1, 10- > 1, 12- > 1, 18- > 1	1, 10, 12, 18	Unknown	1	1	3
4	J. Educ. Comput. Res.	Jang et al. (2017)	9- > 1,2,3, 11- > 1,2,3, 12- > 1,2,3	9, 11, 12	Unknown	1, 2, 3	1	3
5	J.Inter professional Care	Johnson & Howell (2017)	1- > 1, 10- > 1, 16- > 1	1, 10, 16	Ecuador	1	2	2
6	Journal of Science Education And Technology	Karahan & Roehrig 2015	1- > 1, 12- > 1, 16- > 1	1, 12, 16	USA	1	1	3
7	Teach. Learn. Med.	Keister & Hansen (2017)	1- > 1, 12- > 1	1, 12	USA	1	1	3
8	International Journal of Research in Educ.& Sci.	Mahanin et al. (2017)	16- > 1, 17- > 1	16, 17	Brunei	1	1	3
9	International Journal of Science and Mathematics Educ.	Ohle et al. (2016)	1- > 1, 12- > 1,3, 17- > 1	1, 12, 17	Germany	1, 3	1	3
10	Comput. Appl. Eng. Educ.	Perini et al. (2017)	12- > 1,3, 16- > 1	12, 16	Italy	1, 3	1	3
11	IAFOR Journal of Education	Spence & Tao (2016)	1- > 1, 16- > 1	1, 16	Japan	1	1	2
12	Computers in Human Behavior	Taub et al. (2017)	8- > 1, 9- > 1	8, 9	USA	1	1	1
13	International Journal of Technology and Design Educ.	Van Niekerk et al. (2010)	1- > 1, 10- > 1	1, 10	South Africa	1	1	2
14	BMC Medical Education	Wong et al. (2016)	10- > 3, 12- > 3, 16- > 3	10, 12, 16	China	1	2	3
15	BMC Medical Education	Wong (2014)	1- > 3, 10- > 3	1, 10	Canada	3	1	2
16	British Journal of Educational Psychology	Yang & Chen (2015)	1- > 1,3, 10- > 1,3, 12- > 1,3, 16- > 1,3	1, 10, 12, 16	Taiwan	1	1	3
17	Educational Studies in Mathematics	Yau et al. (2016)	1- > 1, 10- > 1, 16- > 1	1, 10, 16	Hong Kong	1	1	2
18	Eur. J. Dent. Educ.	Bowman (2017)	10- > 2, 12- > 1,2	10, 12	UK	1, 2	1	2
19	Educational Technology & Society	De Witt et al. (2017)	9- > 1, 10- > 1, 17- > 1	9, 10, 17	Malaysia	1	2	1
20	J. Educ. Comput. Res.	Jang et al. (2017)	9- > 1,2,3, 11- > 1,2,3, 12- > 1,2,3	9, 11, 12	Unknown	1, 2, 3	1	3
21	J. Interprofessional Care	Johnson & Howell (2017)	1- > 1, 10- > 1, 16- > 1	1, 10, 16	Ecuador	1	2	2
22	BMC Medical Education	Wong et al. (2016)	10- > 3, 12- > 3, 16- > 3	10, 12, 16	China	1	2	3
23	Electronic Journal of E-Learning	Yap et al. (2016)	17- > 1, 17- > 13, 13- > 1, 13- > 3	17, 13	Malaysia	1, 3	1	3

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Table 2: Summary of the respective modality, its Type and focus in the reviewed publication (count...)

S.no	Journal	Reference	Modality (- > focus)	Type (Modality)	Country (conducted study)	Focus (1:Cognition, 2:Emotion, 3:Motivation)	Learning Type(1:Individual , 2:Collaborative 3: Mixed)	Method(1:Qualitative, 2:Quantitative 3:Mixed)
24	Educational Studies in Mathematics	Yau et al. (2016)	1- > 1, 10- > 1, 16- > 1	1, 10, 16	Hong Kong	1	1	2
25	Nurse Educ. Today	Zakari et al. (2014)	1- > 1, 10- > 1, 16- > 1	1,10,16	Unknown	1	1	2

6 OVERVIEW OF STUDY SENTIMENTAL ANALYSIS & OPINION MINING

The Polarity categorization has been achieved using thumbs up/thumbs down approaches and Document categorization is based on feelings, either positive or negative, according to this approach given by Pang et al. (2002)., furthermore Popescu et al. (2005) introduced OPINE, which provides product feature recognition, opinion identification regarding product characteristics, opinion polarity identification, and opinion rank. The system is quite effective, according to the tentative outcome. Table 3 displays the outcomes, as well as a discussion of various methodologies and results. The field of sentimental Analysis (SA) has advanced strategies to perform Opinion Mining (OM) or SA tasks. The supervised & unsupervised machine learning approaches is to be use to performs various task, these approaches which are describe below

Table 3 summary of the database techniques and oval all performance

Reference:	Research (focus)	Database	Methodologies	Precision or recall: accuracy or F-measure	Outcome
Martínez-Cámara et al.(2011)	Classification, Polarity (Spanish Corpus)	Spanish film Corpus (Review)	SVM, Naïve, Bayes, BBR, KNN,C4.5	– 87.21%,87.01 % 87.21%	Successful Sentimental categorization
Habernal et al.(2014)	Classification of Polarity (Czech Corpus)	Czech social media corpus	Maximum entropy (MaxEnt),SVM	– 69.0%	Successful sentiment classification
Smailović et al. (2014)	Predictive analysis of sentiment analysis	Twitter Feeds for selected companies	SVM	– 0.645 64.05%	Check prices Forecasting in Futures
Popescu et al.(2005)	Explicit features extraction and polarity identification	Amazon	Unsupervised information extraction system, relaxation labeling	– 79% 76%	Review polarity identification and Presentation
Hari Krishna, Ali Akba et al(2017)	Sentiment Analysis based on Feature based approaches	SVM & co-reference Resolution	Training Dataset of Product Review	73.6%	Feature Based Approach SVM and co-reference Resolution
Monika Negi, Kanika Vishwakarmaet al(2017)	A Study on Twitter's Sentiment Analysis with, ML Algorithms	Naïve Bayes, SVM, Maximum Entropy	Twitter Dataset	86.4% 73.5% 88.97%	Novel Machine Learning Algorithms Python
ShivDhar,S.Pednekar et al (2018)	Sentiment Analysis by Neural Networks	Convolutional Neural Network	Review on Twitter Data and Product Data	74.15% 64.69%	ANN, Review opinion polarity identification

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Reference:	Research (focus)	Database	Methodologies	Precision or recall: accuracy or F-measure	Outcome
Chae Won Park, Dae Ryong Seo(2018)	Sentiment Analysis of Twitter Corpus linked to Artificial Intelligence based Assistants[70]	Valence Aware Dictionary and Sentiment Reasoner (VADER)	Electronic product review	87.4%	A Feature Based Approach electronic product review
Kudakwashe Zvarevashe, Oludayoet al (2018)	A framework for hotel reviews using sentimental analysis & opinion mining	Naive Bayes	Reviews Hotels from Opinion Rank	83.5%	Sentimental Review on rank judge by opinion
Satuluri Vanaja, Meena Belwal(2018)	E-Commerce based Sentiment Analysis on Data	Naïve Bayes, SVM	Amazon Customer Review Data	90.423% 83.43%	Aspect-Level Sentimental Analysis on E-Commerce
Sayali,Zirpe, BelaJoglekar (2017)	A research survey to detect Polarity Shift in Sentiment Analysis:	Supervised & Lexicon based ML	Product Review	84.6%	Review approaches of Sentiment Analysis for Polarity Shift for product

For functions other than the classification of numerous observations and its types, such as SA and other different methods, these methods are described and open in research RQ3 in the section that are as follows.

6.1 RQ3. Results for research question 3

In response to RQ3, we have determined the machine learning task for SA. The classic fact-based analysis includes information on summarizing critical text as well as on more general topics like document classification and polarity detection and emotion shift. As we know there are three types of reviews regular, comparative, and suggestive that ensure the use of reviewers' use of these types have been found. Contrary to popular notion, comparative opinion research is still in its early stages, yet it is nonetheless crucial. A successful method that has a solid foundation in the relevant datasets is the comparative classification technique published by (Jindal and Liu in 2006). Even while comparative opinion research is still in its early stages, its importance and the value of comparisons for consumers should not be understated. The comparative sentence identification method put out is a successful method that excels for the datasets listed below.

Table 4: Summary of the data set, Technique and Output

References	Research (focus)	Review Data-set	Methodologies	Outcome
Dheraj, Olsher, Cambria & Kwok (2012)	Commonsense, reasoning Conscious & unconscious	Live Journal Patient Opinion	Activation of Sentic	Brain-inspired model for computational approach
Hussain ,Benson,Cambria & Eckl(2012)	Elicitation of Sentics &Semantic data	Patient Opinion	Sentic PROM	Health assessment System in Semi-structured data
Cambria etal.(2014)	Common & commonsense Knowledgebase	Pro based Concept Net is anette corpus of Open Mind	Use Semantic scaling multidimensional method	Open-domain system for opinion and sentiment analysis

References	Research (focus)	Review Data-set	Methodologies	Outcome
Cambria et al.(2013) Poriaetal et al (2014)	Concept-level Framework for affective commonsense reasoning in Text data processing	Patient Opinion Social enterprise pioneering (ISEAR - International Survey of Emotion Antecedents And Reactions)	Biologically inspired Opinion mining engine Fuzzy c-means Clustering & SVM classification	SOTA framework for Opinion mining Engine
Cambria et al.(2013) Poriaetal et al (2014)	Concept-level Framework for affective commonsense reasoning in Text data processing	Patient Opinion Social enterprise pioneering (ISEAR - International Survey of Emotion Antecedents And Reactions)	Biologically inspired Opinion mining engine Fuzzy c-means Clustering & SVM classification	SOTA framework for Opinion mining Engine
Loia and Senatore (2014)	Framework to extract emotions(s)& sentiment(s)	Twitter and New York .times	Fuzzy logic	Prototype develop to identify emotions from text
Satuluri Vanaja, Meena Belwal (2017)	Method of Short Texts in Micro blogging in Sentiment Analysis	Language Technology Platform(LTP) used for craving syntax analysis	COSA 2014(BBC Data Set)	Sentiment Analysis Method for dependency syntax analysis
PreslavNakov, Alan Ritter et t al (2016)	SemEval-2016 Task 4: Sentiment Analysis in Twitter	Twitter Dataset	SVM	Sentiment Analysis in Twitter‖
Pierre FICAMOS, Yan LIU (2016)	Topic-based approach for Sentiment Analysis on Twitter Data[74]	Twitter Dataset	SVM	Topic based Sentiment Analysis for polarity
Alexander Pak, Patrick Paroubek (2010)	Twitter as a Corpus for S.A & Opinion Mining	SRF	Twitter Dataset	Use twitter Corpus for SA & Opinion Mining

7 CONCLUSION

First, this paper is based on what we found; we concluded that there is much to learn about multimodal data in many different learning domains. We have briefly outlined how different machine learning techniques can be used to develop answers to a range of real-world problems online with our goal. This would give people a sense of what multimodal data can and cannot do in all areas of learning. In multimodal data research, we focus on how to learn and collect data in multiple types from blended learning environments that could help researchers in the future better understand the extensive social, cognitive, in addition, emotional procedures and learning. Even though the majority of research collected multimodal data in the campus, several other studies also did so in online or mixed-learning environments. We did an efficient survey of the qualities of ML strategies to show the viewpoint of multimodal data analysis for intelligent systems and how it is capable of being used for information and its effectiveness. An AI model must successfully implement both learning algorithms before it can assist users in making wise judgments for the complex target application's knowledge and real-world data that must use to prepare for training a learning algorithm .To emphasizes we further discussed the breadth of ML methodologies' applicability to various specific problems and several popular application areas. In general, We think that tackling each of the issues mentioned in this study would not only increase ML-enabled conversation understanding but also boost dialogue systems' effectiveness by taking emotional information into account. We think that our research into Machine learning-based solutions provides new opportunities that can be used for technical reference in futuristic research by the industry and academic and other professionals. It would be out of the ordinary to compare how multimodal data is used in different fields to fill its full potential.

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