An Investigation on Sentiment Analysis

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Abstract- Sentiment analysis is useful for multiple tasks including customer satisfaction metrics, identifying market trends for any industry or products, analyzing reviews from social media comments. These kinds of data assets, which are a broad stage of people's sentiment, suggestions, input, and audits, are viewed as intense witnesses and have become a valuable resource for big industries, research and technology markets, news service providers, and numerous domains where sentiment analysis became a useful tool. This paper discusses on deep learning algorithms applied in recent years for sentiment analysis. The main goal of this paper is to analyze how deep learning research is growing in different application areas and can be helpful for sentiment analysis.

Keywords- Computer Vision, Deep Learning, Machine Learning, Natural Language Processing Sentiment Analysis

I. INTRODUCTION

Sentiment analysis which is also called opinion mining is a part of the text mining which to learn how to analyze opinion, sentiment, evaluation, assessment, attitude, and human emotion to an entity such as products, services/service, organization/group, individual, issue, topics, etc. Other names of sentiment analysis are often called: sentiment analysis, opinion mining, opinion extraction, sentiment mining, and others. Sentiment analysis is categorized into two types of the resulting opinion: positive opinion and negative opinion. In some research are categorizes into three types: positive opinion and negative opinion added with a neutral opinion[1]. Together with the expansion in the entrance to innovation and the Internet, the ongoing years have demonstrated a consistent development of the volume of client created substance on the Web and furthermore the development of client created content in sites and interpersonal organizations, for example, Twitter, Amazon, and Trip Advisor, has prompted an expanding intensity of informal organizations for communicating conclusions about administrations, items or occasions, among others. This propensity, joined with the quick spreading nature of substance on the web, has transformed online conclusions into an extremely important asset [2]. In this unique situation, numerous Natural Language Processing (NLP) assignments are being utilized keeping in mind the end goal to investigate this monstrous data. Specifically, Sentiment Analysis (SA) is an inexorably developing assignment, whose objective is the arrangement of assessments and slants communicated in content, created by a human part.

The assorted variety of points secured by this information (additionally containing articulations of subjectivity) in the new literary composes, for example, web journals, for a, miniaturized scale sites, has been turned out to be of colossal incentive to an entire scope of uses, in Economics, Social Science, Political Science, Marketing, to say only a couple[3].

The exploration in this field is quickly grabbing and has pulled in the consideration of the scholarly community and industry alike. Joined with progresses in flag handling and AI, this exploration has prompted the improvement of cutting edge savvy frameworks that plan to distinguish and process emotional data contained in multimodal sources. Be that as it may, the lion's share of such best in class structures depend on preparing a solitary methodology, i.e., content, sound, or video. Also, these frameworks are known to show impediments regarding meeting power, exactness, and generally execution necessities, which, thus, enormously confines the handiness of such frameworks in true applications[4].

The progressions from informal communities to online interpersonal organizations are empowering individuals to discuss their sentiment and assessments, and all the more significantly to share and spread their musings, with other individuals with no topographical obstruction. This unrest has consequently added to the ascent in a novel estimation examination undertakings from a machine adapting/profound learning and characteristic dialect preparing perspective[5].

For Sentiment analysis, the sample classification methods used are machine learning techniques with Support Vector Machine (SVM) and Naive Bayesian Classifier (NBC) combined with feature extraction approach, unigram, bigram and Part of Speech (POS) etc.

Deep learning procedures for Sentiment Analysis have turned out to be exceptionally mainstream. They give programmed include extraction and both more extravagant portrayal capacities and preferable execution over conventional component based methods. Conventional surface methodologies depend on complex physically extricated highlights, and this extraction procedure is a principal question in include driven techniques. These since quite a while ago settled methodologies can yield solid baselines, and their prescient capacities can be utilized related to the emerging profound learning strategies[2].

In this work we present the article as takes after similarly as with the latest progressions in regards to feeling examination in online informal communities. In Section 2 the key components that portray the online informal organizations for sentiment analysis is depicted. In Section 3 a writing audit of sentiment examination from a machine learning and deep learning point of view is exhibited, concentrating on the idea of the interpersonal organizations, which are really wealthy in casual dialects and connections among clients. And most recent works utilizing profound learning are tabulated. In Section 4 future bearings for the up and coming age of supposition investigation with profound learning is given.

II. SENTIMENT ANALYSIS

General steps for Sentiment analysis[6].

1) Sentiment Extraction

- a) Evaluation of object Extraction
- b) Emotional word or polarity word Extraction

2) Sentiment Classification

- a) Subjective & objective classification
- b) Sentiment Classification through Machine learning

Everybody can express his own particular assessment about everything that may be for instance an administration, an item, an occasion or a point, which is called target question or element. The creators of a communicated assessment are known as sentiment holders or feeling sources. Assessments can be categorized as one of these two gatherings: normal feelings and near conclusions. Normal sentiments are known as assessments in the exploration writing. Near suppositions express inclinations of the sentiment holder in connection to at least two target objects in light of their perspectives. A sentiment introduction can be sure, negative or unbiased which are otherwise called polarities or semantic introductions [7][8][9].AI is the capacity of a machine, for

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example, a computerized PC or a PC controlled robot to perform undertakings that are usually connected with keen creatures, for example, basic leadership, discourse acknowledgment, visual discernment and dialect interpretation.

III. DEEP LEARNING

Within a few years, deep learning will greatly influence analytics tools and practices. Its effect has already been felt by smartphone users: deep learning changed speech recognition with Apple's Siri and Google's Voice from a curiosity to a usable feature. There are almost weekly breakthroughs in image recognition, speech-to-text conversion, machine translation, and in many more areas.

Three main components for developing a machine-learning model:

■ Training data — A cornerstone of ML. This data contains the information to learn from.

■ Learner algorithm — An algorithm (or a set of algorithms) to interpret the training data.

■ Output — A prediction or insight, derived from data.

Deep learning is a minor departure from machine learning: business issues are illuminated through the extraction of information from information. Deep learning grows standard machine learning by enabling middle portrayals to be found. This middle of the road portrayals enable more mind boggling issues to be handled and others to be conceivably unraveled with higher precision, less perceptions and less unwieldy manual tweaking. A relation between deep learning and machine learning is shown in figure 1.

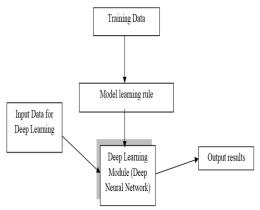


Figure 1. Deep learning and Machine learning relationship flow diagram

With deep learning, a computer model can be fed lots of complex data, such as images, speech and text. For example, deep-learning algorithms can analyze retina scans to "figure out" on their own which patterns indicate healthy or diseased retinas (and indicate the specific disease). The "figuring out" process relies on brute-force, high-performance computing

and can, to some extent; render obsolete the tedious handcrafting of features and data preparation [48].

Deep learning (often also called deep neural nets) is an impressive technology area with wide applicability across many industries, but solutions require significant skills. Deep learning is here to stay. It is currently the most promising technology in predictive analytics for previously intractable data types for machine learning, such as images, speech and video. It also can deliver higher accuracy than other techniques for problems that involve complex data fusion. Using deep-learning technology has major implementation risks, magnified by inadequate data, opaqueness of models, the scarcity of relevant data science and programming skills, the need for high-performance compute infrastructure, and uncertain or uninformed executive sponsorship.

Training a DNN, which may have thousands or millions of parameters, relies on a highly iterative and computationally intensive procedure, using "gradient descent" and "backpropagation," heuristic. which are numerical optimization techniques. These optimizations have only become feasible today on such a broad scale because of the recent breakthrough in high-performing graphics processing unit (GPU) architectures.

a. Deep Learning Applications

Deep learning is well suited to tasks where supervised learning is difficult, either because labeled data is not available or because there are too many variables to model. Applications extend to any task involving the written word, sight, and sound as shown in figure 2.

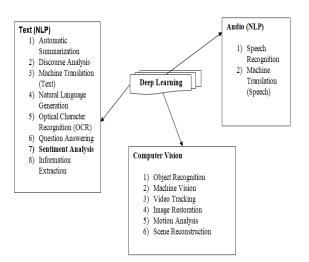


Figure 2. Deep Learning Applications

Deep learning platforms that assist users in creating their own deep-learning solutions is shown in figure 3:

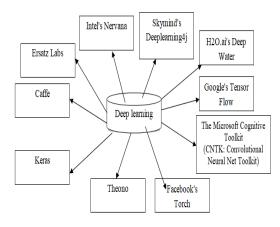


Figure 3. Deep Learning Frameworks

Deep-learning cloud platforms that allow users to run deeplearning experiment in the cloud is shown in figure 4:

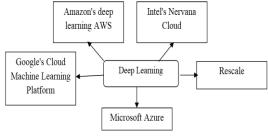


Figure 4. Deep Learning Cloud platforms

Packaged applications or SaaS solutions or APIs providing prefabricated solutions using deep learning:

- Algorithmia's Deep Learning APIs
- Clarifai's Image & Video Recognition APIs
- Google's Machine Learning APIs, IBM Watson Developer Cloud
- Microsoft's Cognitive Services APIs
- Nvidia's Drive PX2

Hardware systems facilitating high-performance compute necessary for deep learning:

- Nvidia's diverse offerings
- Intel's AI ecosystem (Intel Deep Learning SDK)
- AMD's Radeon Instinct

The general misconceptions on Deep Learning are as follows

- Deep Learning is not good for old fashioned AI
- Deep Learning is different from Machine Learning
- Deep Learning does not mimic Biological Brains
 - 1) Deep Learning is not Artificial General Intelligence
 - 2) Deep Learning is not just Math
 - 3) Deep Learning is not statistics
 - 4) Deep Learning is not Big Data
 - 5) Deep Learning is not understood by Data Scientist

6) Deep Learning is not just ANN or Multi Level Perceptron (MLP)

The below figures 5 to 9 gives the Scopus analysis of deep learning algorithms for sentiment analysis

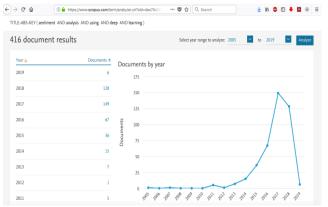


Figure 5. Deep Learning Analysis (Till date)

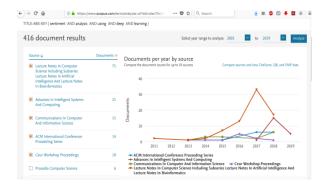


Figure 6. Deep Learning for sentiment analysis publications progress

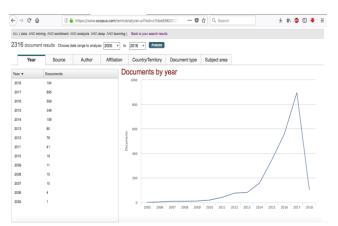
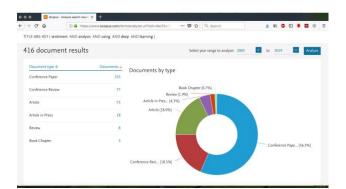
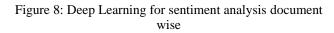
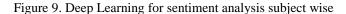


Figure 7. Deep Learning for sentiment analysis publications progress by year wise





| Scopus - A | Analyze search result: X + | | |
|---------------------------------|------------------------------------|--|----|
|) → ሮ ≙ | 0 🔒 https://www.scopus.com/ter | m/analyzer.uni7sid=dec79a1: 🛡 🏠 🔍 Search 👱 🕪 🕏 🖸 🐥 🖬 😵 | |
| TITLE-ABS-KEY (sentim | nent AND analysis AND using AND de | ep. AND learning) | |
| 416 documer | nt results | Select year range to analyze: 2005 💌 to 2019 💌 Analyz | ze |
| Subject area \downarrow | Documents 🔶 | Documents by subject area | |
| Computer Science | 386 | | |
| Mathematics | 126 | Other (2.6%) | |
| Engineering | 94 | Materials Scien (1.0%) | |
| Social Sciences | 28 | Medicine (1.2%) Arts and Humani (1.6%) | |
| Decision Sciences | 27 | Business, Manag (1.9%) Decision Scienc (3.7%) | |
| Business, Managem Accounting | ent and 14 | Social Sciences (3.8%) Engineering (12.9%) | |
| Arts and Humanities | s 12 | | |
| Medicine | 9 | Mathematics (17.3%) | |
| Metalala Calence | | | |



The below table 1, explains the recent sentiment analysis technique's with deep learning works.

Table 1. Sentiment analysis technique's with deep learning

| S | Title | Advantages | Remarks | |
|----|--|--|--|--|
| No | | | | |
| 1 | Comparati ve experiment s using supervised learning and machine translation for multilingua 1 sentiment analysis[3]. | It was discovered that a low nature of the interpretation prompts a drop in execution, as the highlights separated are not sufficiently useful to take into account the classifier to learn. | The proposed approach relies upon the accessibility of the interpretation motors for the required dialects. | |
| 2 | Ensemble application of convolutio nal neural networks and multiple kernel learning for | The proposed structure beat the cutting edge display in multimodal slant examination look into with an edge of 10–13% and 3–5% precision on extremity identification and feeling acknowledgment, separately. The paper additionally proposed a broad investigation on choice level | The regular multimodal influence information examination structure is well fit for removing feeling and conclusion from various datasets. | |

| | multimodal | combination. | | | Prediction | nostalgic investigation with the | information'. They |
|---|---------------------------|--|--|----|-------------------------|--|--|
| | sentiment | contoniation | | | Accuracy | working of advanced wistful | utilized morpheme |
| 3 | analysis[4]. Enhancing | Proposed a few models where | Work took the benefit | | Improveme nt using | word reference for each organization and was | examination and wistful investigation |
| 3 | deep | exemplary hand-created | of the troupe of | | Sentiment | conceivable to apply the | to make digitize it. |
| | learning | highlights are joined with | existing customary | | Analysis | strategy for wistful examination | - |
| | sentiment analysis | naturally extricated implanting highlights, and in addition the | assumption classifiers, and additionally the | | and Machine | during the time spent refining information to use for machine | |
| | with | troupe of analyzers that gain | mix of bland, | | Learning | learning | |
| | ensemble | from these changed highlights. | conclusion prepared | | based on | C . | |
| | techniques in social | | word implanting and | | Online Neuro[12] | | |
| | in social application | | physically made highlights. | 9 | News[12]. Sentiment | The proposed approach is | Contingent upon the |
| | s[2]. | | 5 5 | Í | Analysis | successful in characterizing | point, the best |
| 4 | Sentiment | The regulated models that can | The vast majority of | | through | content reports as having a | performing |
| | Analysis in Social | use characteristic dialect are entirely centered around | the work with respect to extremity order as a | | Machine Learning: | place with negative or positive sentiment in regards to the | calculation for every theme fluctuates. |
| | Networks: | express feelings | rule thinks about | | An | given point. | Authors utilized 10- |
| | a Machine | | content as novel data | | Experiment | | overlap cross- |
| | Learning Perspective | | to deduce feeling, neglecting those | | al Evaluation | | approval in every one of the analyses |
| | [5]. | | informal organizations | | for | | keeping in mind the |
| | - | | are really organized | | Albanian[7 | | end goal to get |
| 5 | Classifiert | To ophonos the environment of | conditions. | |]. | | dependable characterization |
| Э | Classificati on of | To enhance the arrangement execution, Authors proposed a | The half breed of different regulated | | | | exactness |
| | sentence | cloud coordinate the help | techniques to upgrade | 10 | Combining | To assess the technique, | Introduced formal |
| | level | vector machine, Navie bayes | the order precision for | | Formal Logic and | Authors utilized for element level opinion investigation as | intelligent strategy for profound auxiliary |
| | sentiment analysis | and neural system calculations alongside joint division | expansive corpora of sentence level or | | Machine | an option in contrast to | examination of the |
| | using cloud | approaches has been proposed | report level notion | | Learning | unadulterated machine learning | grammatical |
| | machine | to order the simple positive, | arrangement has been | | for | strategies for slant examination. | properties of writings |
| | learning techniques[| positive, impartial, negative and extremely negative | proposed as future work to enhance the | | Sentiment Analysis[1 | | utilizing machine learning strategies for |
| | 6]. | highlights all the more | execution. | | 3]. | | productive linguistic |
| | | successfully utilizing vital | | 11 | Twitter | Authors acquainted a | labeling. Authors connected |
| 6 | A survey | component choice. Authors found that a large | Scarcely any | 11 | Sentiment | methodology with choice of | Bigram, Unigram, |
| | on | portion of the papers utilize | investigations utilized | | Analysis | another list of capabilities in | Object-situated |
| | sentiment analysis of | traditional machine learning techniques. Notwithstanding, | vocabulary construct method that depends | | Using Machine | light of Information Gain, Bigram, Object situated | highlights as a powerful list of |
| | scientific | because of impediments of | with respect to | | Learning | extraction strategies in | capabilities for feeling |
| | citations[1 | execution and manual | supposition | | Techniques | estimation investigation on | investigation |
| | 0]. | component determination in | vocabularies, for example, | | [14]. | person to person communication side. | alongside a decent memory for settling |
| | | machine learning, they trust that later on half and half and | SentiWordNet. They | | | communication side. | highlights better. |
| | | profound learning strategies | rely upon static | 12 | Learning | The proposed system with 4% | The Authors |
| | | can deal with the issues of | 6 | | Higher- | change in precision watched for | consolidated more |
| | | logical reference slant investigation all the more | or words and accepted that the word that isn't | | Level Features | subjectivity order and enhanced the outcomes accomplished for | elevated amount highlights learned by |
| | | productively furthermore, | in the dictionary isn't | | with | opinion grouping over models | CRBM additionally |
| | | dependably. | considered. One of the | | Convolutio | prepared without our larger | enhanced the |
| | | | restrictions of these methodologies is | | nal Restricted | amount highlights. | precision. Specifically, including |
| | | | content autonomous | | Boltzmann | | the CRBM-layer1 |
| 7 | Use of Machina | The investigation must be | The impartial opinion | | Machines (CRBM) | | highlights is by all |
| | Machine Learning | viewed as respectable if there is an extraordinary polarizing | in the tweets quantitatively | | (CRBM) for | | accounts very powerful. |
| | Algorithms | opinion, for example, over 80% | dominates the positive | | Sentiment | | 1 |
| | and Twitter | tweets are demonstrating a | and negative | | Analysis[1 | | |
| | Sentiment Analysis | positive supposition about the stock, and at that point it very | assumption | 13 | 5]. Cross | Authors plans to characterize | Navie Bayes |
| | for Stock | well may be finished up with | | 15 | Domain | strategies to defeat the issue of | Multinomial, SVM |
| | Market | some sureness that the stock | | | Sentiment | lower exactness in cross-area | with straight bit are |
| | Prediction[11]. | value bound to go up. | | | Analysis Using | notion grouping utilizing diverse systems and taking the | superior to different classifiers for cross |
| 8 | Stock | By utilizing the morpheme | Authors anticipated | | Different | advantage of being a quicker | area |
| | Prediction | analyzer it was conceivable to | change of stock cost | | Machine | technique. | |
| | and | enhance the precision of | with utilizing 'News | | Learning | | |

| | Taabaia | | 1 | | Dumosc | | broadly useful T-144 |
|----|---------------------------|--|---|----|------------------------|---|---|
| | Techniques [16]. | | | | Purpose Twitter | | broadly useful Twitter feeling investigation |
| 14 | Sentiment | Writers capable locate a light | Arabic dialect requires | | Sentiment | | which can radically |
| | Analysis | weight feeling examination | significantly more | | Analysis | | diminish the measure |
| | for Arabic | approach for informal | research particularly | | with Deep | | of manual comment |
| | Reviews in | communities' surveys | in the preprocessing | | Neural | | that is expected to |
| | Social Networks | composed in Arabic dialect. | stage. | | Networks[22]. | | accomplish adequate outcomes. |
| | Using | | | 20 | Logical | The proposed strategy uses | The proposed work |
| | Machine | | | | Entity | machine learning systems for | power is right now |
| | Learning[1 | | | | Level | proficient syntactic labeling. | deficient for most true |
| 15 | 7]. | TT 1 | | | Sentiment | | applications. |
| 15 | A Deep Architectur | The neural system models utilized as sub-modules | The proposed engineering makes a | | Analysis[2 3]. | | |
| | e for | alongside word installing, CNN | blend of CNN and | 21 | A Real- | The proposed framework not | The proposed work |
| | Sentiment | and LSTM. Profound Balanced | LSTM, with cautious | | Time | just group records and give a | conveyed an Artificial |
| | Analysis | model accomplished the best | investigation and | | Machine | pertinent data yet additionally | Neural Network and |
| | of News | exactness for the proposed | clarification of | | Learning | improves ventures of various | k-Mean calculation |
| | Articles[18]. | work. | methods of reasoning when fathoming the | | Approach for | methods utilized for Sentiment Analysis and expands the | for Sentiment Analysis. |
| | 1. | | issues of news | | Sentiment | performance(reducing memory | |
| | | | articles. | | Analysis[2 | and processor usage) by | |
| 16 | Detecting | Authors proposed a profound | The trials | | 4]. | altering the conveyed | |
| | Twitter Users' | neural system (DNN) approach (back spread calculation) is | demonstrated that the profound learning | 22 | Compariso | calculations. The proposed work examines | It is seen that given a |
| | Opinions | connected to Arabic tweets to | outflanks other | 22 | n of | the execution of three machine | basic arrangement of |
| | of Arabic | two distinct spaces, DNN is | machine learning | | Machine | learning (ML) procedures | sub-errands (TF-IDF |
| | Comments | actualized to identify clients' | calculations. | | Learning | including Naïve Bayes (NB), | and stemmed words) |
| | During | mentality in a day and age of | | | Approache | Support Vector Machine | in removing highlight, |
| | Various Time | two years for each dataset. | | | s on Arabic Twitter | (SVM) and Decision Tree (DT) when utilized on Arabic feeling | Arabic conclusion investigation on two |
| | Episodes | | | | Sentiment | examination in light of a | classes of |
| | via Deep | | | | Analysis[2 | straightforward separated | suppositions, will |
| | Neural | | | | 5]. | component. | performed better if |
| | Network[1 9]. | | | | | | DT is utilized rather than SVM and NB. |
| 17 | Applying | Authors contrasted the | By utilizing an | 23 | Sentiment | The Authors attempted to break | There are sure issues |
| | Machine | outcomes and the assistance of | adequately extensive | | Analysis in | down the twitter posts about | while managing |
| | Learning | various classifiers. Mechanized | and great preparing | | Twitter | electronic items like mobiles, | distinguishing |
| | Techniques for | grouping makes it less demanding and quicker to | dataset precision of forecast can be moved | | using Machine | PCs and so on utilizing Machine Learning approach. | enthusiastic watchword from |
| | Sentiment | investigate information when | forward. | | Learning | Machine Learning approach. | tweets having various |
| | Analysis in | contrasted with manual process | Tor wardi | | Techniques | | catchphrases. It is |
| | the Case | which would expend critical | | | [26]. | | hard to deal with |
| | Study of | measure of time and exertion. | | | | | incorrect spellings and |
| | Indian Politics[20] | | | 24 | Sentiment | The exactness enhanced when | slang words. The gullible byes |
| | | | | 24 | | the semantic investigation | method gave a |
| 18 | Empirical | The best F1-score was acquired | The proposed | | Twitter | WordNet is followed up by the | superior outcome than |
| | Evaluation | by utilizing the pretrained word | demonstrate is really a | | Data Using | above system taking it to | the greatest entropy |
| | of Word | vectors from the CBOW show. | conclusion to-end | | Machine | 89.9% from 88.2%. | and SVM is being |
| | Representa tions on | Besides, Authors saw that utilizing pretrained word | which implies that it doesn't depend on | | Learning Approache | | subjected to unigram show which gave a |
| | Arabic | embeddings with all | designing highlights | | s and | | superior outcome than |
| | Sentiment | models(Glove, Skip-Gram and | considered as tedious. | | Semantic | | utilizing only it. |
| | Analysis[2 | CBOW) enabled the model to | | | Analysis | | |
| | 1]. | enhance altogether its execution over the model | | 25 | [27]. Sentiment | The proposed framework | Authors have thought |
| | | utilized just arbitrarily | | 23 | Analysis of | The proposed framework checks the extremity at the | about two measurable |
| | | introduced word vectors. | | | Malayalam | sentence level, brought about | techniques to be |
| 19 | А | The proposed strategy beat | By Combining | | Film | an exactness of 91%. | specific SVM and |
| | Comparati | haphazardly chosen preparing | profound | | Review | | Conditional Random |
| | ve Study of Uncertaint | information when the measure of preparing information | convolutional neural systems with dynamic | | Using Machine | | Filed (CRF) for investigating the |
| | y Based | utilized for the two | learning in view of | | Learning | | notions of Malayalam |
| | Active | methodologies is of equivalent | vulnerability | | Techniques | | motion picture |
| | Learning | size. | inspecting is by all | | [28]. | | surveys. From this |
| | Strategies | | accounts a promising | 1 | | | examination, we have |
| | for General | | methodology for | | | | discovered that SVM |

| | | | outflanks the CRF. | | 34]. | | |
|----|--|--|---|----|---|---|---|
| 26 | Utilizing Machine Learning in Sentiment Analysis: SentiRobo Approach[29]. On Multi- Tier Sentiment Analysis using | The proposed work of SentiRobo prevailing with regards to anticipating the feeling estimation of blended English-Malay tweets in two spaces of Education and Airport Management with exactness rate of 71% and 79% separately. For the proposed work, multi- level model can altogether enhance expectation exactness over the single-level model by over 10%; the change is huge | Authors proposed a directed machine learning calculation for foreseeing the assessment estimation of Twitter substance in two areas of Education and Airport Management. Four classifiers (Naïve Bayes, SVM, Random Forest, and SGD) are utilized for the proposed work. | 32 | A Review on Opinionate d Sentiment Analysis based upon Machine Learning Approach[35]. Combining a Rule- | From the proposed work, it is seen that regulated calculations are more in incline then unsupervised calculations due it higher precision rate, calculation straightforwardness and simple to utilize trademark. | Among the managed systems SVM, NB strategies are generally acknowledged and utilized by the specialists. There is high need to create advance and high innovation SA calculations for social insurance area. Authors found that using the few |
| | Supervised Machine Learning[3 0]. | when tweaked lexicon is utilized. | Shown approaches to tweak parameters, and systems to diminish highlights for assist change. | | based Classifier with Ensemble of Feature | classifier, the outfit of administered classifiers prepared on various sort of highlights tended to the feeling grouping issue adequately and | conclusion vocabularies for preparing instead of substantial explained dataset is successful, |
| 28 | A Personalize d Recommen der System using Machine Learning based Sentiment | The Authors proposed a structure that is actualized will empower the client to look over just those information which he enjoys and not sit idle on the information superfluous to his needs. | Greatest Entropy has the best exactness esteem among all the Sentiment investigation systems. | | Sets and Machine Learning Techniques for Sentiment Analysis on Microblog[36]. | yielded the huge changes over the known related work. | while single managed classifier joined with the administer based classifier. |
| 29 | Analysis over Social Data[31]. A Comprehen sive Survey for Sentiment Analysis Tasks Using Machine | The feeling investigation issue is for the most part utilized by SVM and NB as they serve high estimation ability, and their estimation capacity is referenced for new machine learning systems. | On account of the marked information is costly and elusive, supposition examination in light of managed learning is as yet a testing errand. Then again, it is substantially | 34 | A Machine Learning Analysis of Twitter Sentiment to the Sandy Hook Shootings[37]. | Authors assessed various machine learning approaches and recognized those most appropriate to ordering open estimation towards firearm savagery in light of the Sandy Hook school shooting. Detectable minority of the US populace see abnormal amounts of open firearm possession as a feature of the arrangement instead of part of issue. | Ordering tweets is trying because of the special idea of miniaturized scale blogging with its continuous utilization of casual and informal dialect including slang and emojis. |
| 30 | Learning Techniques [32]. Is Sentiment Analysis an Art or a Science? | The proposed calculation can be prepared on any paired marked dataset and utilized for making forecasts on any content example, for example, | simpler to assemble unlabeled information. Proposed calculation misses the mark when connected to sentences comprising of express | 35 | Stock Market Sentiment Analysis Based On Machine Learning[3 8]. | The Authors proposed work has given a similar investigation of Navie bayes and SVM on the conclusions of the commentators of the share trading system. | Authors saw that advancement techniques can be connected in arrangement to get enhanced outcomes. |
| | Impact of lexical richness in training corpus on machine learning[33]. | blog entries, news articles, announcements, twitter channel, and so forth. | nullification terms. | 36 | Compariso n of Text Sentiment Analysis based on Machine Learning[3 9]. | Authors utilized the VSM model to speak to content, and afterward utilized SVM and ELM with portions to give out the aftereffect of arrangement. Their principle task to the informational index was cleaning, Word division, availing atta wards hicklight | Proposed ELM with bits technique for passionate extremity examination of Chinese content is more viable. |
| 31 | Domain Based Sentiment Analysis in Regional Language- Kannada using Machine Learning Algorithm[| The proposed work depends on assessment investigation in Regional dialect particular to films utilizing machine learning calculation for arrangement and give an examination between investigation utilizing direct Kannada dataset and machine interpreted English dialect. Choice Tree Classifier is utilized for the proposed work. | Investigating test information in provincial dialect gives better precise outcomes contrasted with Machine Translated English Language. | 37 | Deep Learning Approach for Sentiment Analysis of Short Texts[40]. | expelling stop words, highlight determination and order. Authors proposed a neural dialect model to conquer the weaknesses in conventional and profound learning techniques. Proposed work joined the convolutional and intermittent layer into a solitary model over pre-prepared word vectors, to catch long haul conditions in | It is seen that utilizing LSTM as an option for the pooling layers in CNN gives the model upgrade to catch long haul conditions. |

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| | | short messages all the more | | | Perinatal | |] |
|-----|--------------------------|---|---|--|------------------------|--|---|
| | | productively. The proposed | | | Depression | | |
| | | ConvLstm accomplished | | | [46] | | 1 1 5151 |
| | | equivalent exhibitions with less parameter on slant investigation | | 44 | Deep Recurrent | Authors utilized two methodologies of profound | the proposed RNN approach is contrasted |
| | | undertakings. | | | neural | repetitive neural networks | with other related |
| 38 | A Neural | The time required for building | The proposed | | network vs. | (RNN) and bolster vector | methodologies |
| | Word | the whole notion display was | arrangement permits | | support | machine (SVM) are actualized | utilizing the same |
| | Embedding | around 8.5 hours (single center | overseeing | | vector | and prepared alongside lexical, | dataset for the |
| | s Approach for | proportionate) on a server furnished with a twofold | vulnerability related with each component; | | machine for aspect- | word, syntactic, morphological, and semantic highlights. | assignments T1 and T3. Examination |
| | Multi- | XeonX5650 and 32 Gb of | nonetheless, then | | based | and semance ingringing. | results demonstrate |
| | Domain | RAM. While, amid the testing | again, the intricacy of | | sentiment | | that RNN approach |
| | Sentiment | session, on a similar machine, | the general | | analysis of | | beats other related |
| | Analysis[4 | the calculation of a solitary record extremity required a | engineering will increment. | | Arabic hotels' | | profound learning work in assignment |
| | 1]. | normal of 658 ms. | increment. | | reviews[47 | | T3. (T1: perspective |
| 39 | А | Proposed multilingual | The proposed | |] | | class recognizable |
| | Character- | methodology is significantly | technique is more | | | | proof, T2: angle |
| | based | more sensible, since it utilizes a | precise than a few | | | | conclusion target |
| | Convolutio nal Neural | solitary classifier that can see any of the dialects that were | other profound neural designs while | | | | articulation (OTE) extraction, and T3: |
| | Network | utilized amid preparing. | requiring generously | | | | viewpoint slant |
| | for | Another favorable position of | less learn capable | | | | extremity ID) |
| | Language- | the multilingual setup is that | parameters. | | | | |
| | Agnostic Twitter | the tweet to be investigated can contain terms from particular | | | | IV. CONCLUSION | |
| | Sentiment | dialects without influencing the | | | | | |
| | Analysis[4 | order procedure, which isn't | | T | he developm | nent of sentiment analysis as | a standout amongst |
| | 2]. | valid for the per-dialect | | th | e most dyna | amic research territories of | the most recent 10 |
| 10 | G | arrangement approach. | | ye | ears is beca | ause of various reasons. | In the first place, |
| 40 | Sentiment Analysis | The unsupervised learning step, which was utilized to learn | The proposed strategies in view of | se | ntiment ana | alysis has a wide exhibit of | uses, in relatively |
| | using Deep | vector portrayals of words, is | profound learning | ev | very area. Se | econd, it offers many testing | research issues that |
| | Learning | one of the principle reasons in | would be advised to | ha | we never b | een examined. Third, with | the coming of the |
| | on Persian | better speculation as it utilizes | F-score than NBSVM. | ^{I.} enormous information advancements, we currently have a | | | |
| | Texts[43]. | the semantic data from an extensive corpus of content | One reason could be the utilization of word | e gigantic volume of stubborn information recorded and | | | |
| | | information. | vector portrayals | ef | fectively op | en in computerized frames | on the web. These |
| | | | which is done in an | re | asons have | inspired the ongoing advan | nces in the cutting |
| 4.1 | | | unsupervised way. | ec | lge exhibited | d in this part. | |
| 41 | Big Data: Deep | The Authors watched convolutional neural systems | CNN to extract the sentiment of | | | | |
| | Learning | can beat information mining | authors concerning st | | | Reference | |
| | for | approach in stock feeling | ocks from their words. | | | | |
| | financial | investigation. | | [1 | | Andriansyah et.al, "Compa | |
| | sentiment analysis[44 | | | | | tation of Machine Learning M in Social Media. A Recomm | |
| |] | | | | • | " Adv. Sci. Lett., vol. 20, no. No | |
| 42 | Research | Authors have joined the | For the sentiment | | 2013, 201 | | , rr> |
| | on text | benefits of CNNs and SVM, | characterization | [2 | | e, I. Corcuera-Platas, J. F. Sán | |
| | sentiment analysis | and develops a content slant examination show in view of | assignment, the exactness of utilizing | | | "Enhancing deep learning ser | |
| | based on | CNNs and SVM | the CNN-SVM | | | techniques in social application b. 236–246, Jul. 2017. | s, Expert Syst. Appl., |
| | CNNs and | | display is | [3 | | ur and M. Turchi, "Comparati | ve experiments using |
| | SVM[45] | | considerably higher | Ľ | | d learning and machine transla | |
| | | | than that of CNN and NLPCC-SCDL-best | | | analysis," Comput. Speech Lang. | |
| L | | | models. | | 75, Jan. 20 | | |
| 43 | Sentiment | The Authors utilized the | The proposed work | [4 | | H. Peng, A. Hussain, N. How | |
| | Analysis | profound learning LSTM | incredibly abbreviates | | | e application of convolutional kernel learning for multimodal | |
| | Based on Deep | organize model to screen for perinatal despondency. The | the screening time and lessens the specialist | | | <i>iputing</i> , vol. 261, pp. 217–230, Od | |
| | Learning | technique is more target than | persistent | [5 | | , "Sentiment Analysis in Social N | |
| | and its | the present manual screening | correspondence costs. | | Analysis i | n Social Networks, Elsevier, 2017 | , pp. 91–111. |
| | Applicatio | strategies for the real | | [6 | | urugan, K. R. Sabarmathi, a | |
| | n in Screening | circumstance of perinatal clients. | | | | ation of sentence level sentimen | |
| | for | chefito. | | [7 | | earning techniques," Cluster Com and M. Mane, "Sentiment Anal | |
| · | | | | ٢/ | j ivi. Diud | and wi. wrane, sentiment Ana | iyara unougn macinine |

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