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AI and Machine Learning Assisted Customer Aware Queries: A Comprehensive Analysis to improve User experience based on Natural Language Processing (NLP), Databricks, and Oracle APEX

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Abstract

The customer sentiments are extremely significant to a business, where as positive or negative feedback may influence the sales and uptake of the product in the market and ultimately justify the success of the product in the market. The monthly active users of the major social media sites like Facebook are 2.32 billion monthly active users (MAU) and Twitter 126 million; therefore, the market in learning about the customer mood using social media may be a game changer to a company and may be instrumental in determining the success of the company in the future. Failure to capture the emotions of the users properly may translate to disastrous product failure and loss of the company's reputation of the company. The current systems entail a lot of manual processes like customer surveys, compiling the sentiments and creating Excel reports that are not quite interactive and take a significant amount of time to compile the findings. This research addresses the critical need within the telecom industry for a scalable and real-time framework that classifies customer feedback sentiment in order to help improve service quality and reduce churn. The analysis of hundreds of thousands of unstructured customer reviews collected via Web forms using tools such as Oracle APEX is performed inefficiently using traditional methods. The core challenge is the seamless integration of powerful ML models developed in scalable environments-Databricks-with an existing transactional Oracle Database 19c infrastructure, without compromising system performance or security. The article explore an AI Assisted Customer Aware Analysis to improve User experience based on Natural Language Processing (NLP), Databricks, and Oracle APEX in depth for this a new Sentiment Aware Framework is proposed and will be developed to address this integration gap. The framework design involves using Databricks Machine Learning tools in creating and deploying accurate sentiment models based on classical supervised learning algorithms Naive Bayes (NB) & Support Vector Machines (SVM). The integration work is facilitated by using Oracle REST Data Services (ORDS), which acts as a bridge in handling the customer query submission in real time from the APEX front end to the Databricks ML service, in addition to sentiments to be acted upon. The main contribution of this research is to validate this hybrid, real-time MLOps pipeline in an enterprise environment. This framework provides a concrete roadmap for telecom operators to automate customer feedback classification into positive, negative, or neutral. Quantitative testing proves that the integrated system achieves high accuracy of classification with the required ultra-low latency to support immediate business decisions.

Keywords: Sentiment analysis, emotion recognition, sarcasm detection, explainable NLP, rationalization, transformers, and large language models, BERT, GPT, text classification.

INTRODUCTION

The modern telecom industry is confronted with aggressive competition, an expanding internet infrastructure, and a diverse customer base. In this dynamic environment, a crucial element for the improvement of service quality, while maintaining customer satisfaction by strategically minimizing customer churn, involves understanding customer sentiment. It is often a yardstick for measuring efficiency when a service provider can respond promptly and adequately to customer feedback. In consequence, effective issue resolution, combined with analysis of customer reviews that are usually collected through web-based feedback forms, built on enterprise platforms like Oracle APEX, are significant process underlying the optimization of field operations with a view to creating sustainable revenue streams [1, 2]. Traditionally, the processing of this immense volume of unstructured, text-form customer feedback by telcos proved to be a challenge. Manual analysis of these texts not only proves to be inefficient and costly but is also not very time-conscious, failing to deliver a proactive Customer Service response.

With a bottleneck in this manner, therefore, developing a highly automated and scalable solution for sentiment analysis in this problem proved to be an urgent need where advanced methodologies offered by Machine Learning and Natural Language Processing emerged as efficient tools in this quest [3, 4]. The solution at this stage is based on harnessing the Databricks Machine Learning capability for scaling data analytics and model hosting. Databricks provides a platform with a strong focus on high-throughput data processing and hosting machine learning models as microservices. To make this cloud-native machine learning solution work in perfect sync with the existing system in the organization, the Oracle REST Data Services tool is leveraged. The tool acts as an API gateway and provides a safe and low-latency interface for seamless integration with the existing Oracle Database 19c and APEX front-end environment [5]. Although better sentiment analysis models and more reliable environments for machine learning exist, a vital Integration & Performance Gap remains in the focused telecommunications sector. The proposed framework integrates three distinct academic and technological domains: Sentiment-Aware Search, Machine Learning for Text Analysis, and Hybrid Enterprise System Architecture. This review synthesizes the foundational research in these areas, identifies current limitations, and positions the proposed solution within the existing body of knowledge [6, 7].

SENTIMENT ANALYSIS AND SENTIMENT-AWARE SEARCH

Evolution of Sentiment Analysis (SA)

Sentiment Analysis, or Opinion Mining, is a sub-domain of Natural Language Processing, which aims to identify the attitude (positive, negative, or neutral) of an author towards a particular topic or the net document polarity in general [8, 9]. The early solutions were based on the Lexicon Method, which utilizes predefined word lists evaluated for their subjective polarity. The application of machine learning techniques facilitated a radical evolution in this area. Some of the earliest machine learning solutions in SA were based on supervised learning algorithms such as Support Vector Machines (SVM), Naive Bayes (NB), and Logistic regression, applied to labeled datasets [10, 11]. As evidenced in the literature, these solutions have empirically proved their efficacy in two-class and multi-class text classification [12].

Sentiment-Aware Information Retrieval

Traditional Information Retrieval systems, such as common search engines, mainly focus on lexical matching and relevance ranking. The idea of "Sentiment-Aware Search" arose to incorporate additional sentiment information with respect to a search query or topic of interest into search results [12, 13]. Past research, which utilized approaches such as Oracle Text, concentrated on sentiment score extraction from the hit list of documents obtained by a standard query based on keywords [14, 15]. Although efficient for sentiment analysis in a hit list of documents, this model did not have the facility to:

Analyze Query Sentiment: Conduct sentiment analysis on the query in real time to gauge the intent of the end-user based on query sentiment, whether it is

Dynamic Ranking: As a major input, make use of the predicted sentiment of the query in dynamic ranking to promote relevant action-oriented content, such as support links for negative query sentiment. Where the current state is concerned, the current gap is in providing seamless and real-time integration with a specialized service for sentiment prediction to affect ranking within a transactional search process [16-19].

$$g^t(x) = \sum_{i=1}^{t} y_i \prod_{j=1, j \neq i}^{t} \frac{(x - x_j)}{(x_i - x_j)} \quad \text{Eq (1)}$$

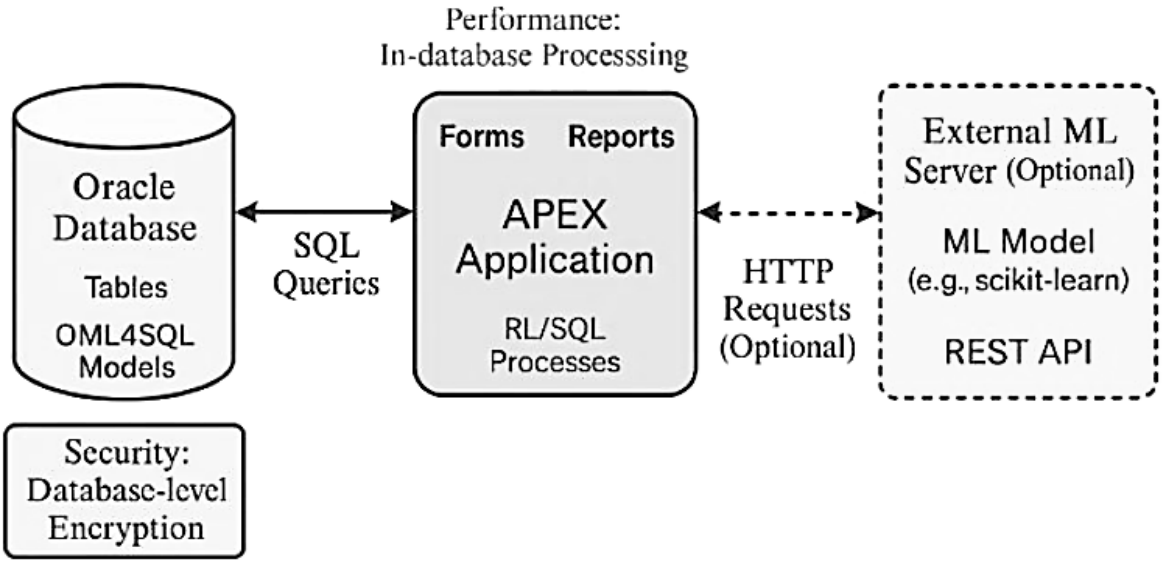

Figure 1.
Generalize Process of Oracle APEX [20]

MACHINE LEARNING MODELS FOR REAL-TIME SENTIMENT PREDICTION

Deep Learning Advancements

The rise of large-scale datasets and distributed computing has led to the dominance of Deep Learning (DL) architectures in sentiment analysis. Models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and particularly Long Short-Term Memory (LSTM) and Bi-directional RNNs (Bi-RNNs) are widely used for their ability to capture contextual meaning and subtle nuances in text [21]. Recent research indicates superior performance from advanced DL

architectures, such as those employing BERT (Bidirectional Encoder Representations from Transformers) or similar large language models (LLMs). These models achieve state-of-the-art accuracy by understanding the context of words in a sentence, which is critical for classifying subtle sentiment in short, often ambiguous search queries [22, 23].

Scalable ML Deployment

The shift to large-scale data requires robust platforms for training and real-time inference. Databricks, built on Apache Spark and Delta Lake, has established itself as a leading platform for unified data and AI workloads [24]. Tools within the Databricks ecosystem, such as specific ML flow functions, demonstrate the platform's capability for performing batch and real-time sentiment analysis [25, 26]. However, the challenge of MLOps is not just model training, but real-time model serving. Integrating the model—once trained on a scalable platform like Databricks—into a production application often requires a sophisticated, low-latency API layer. This necessity highlights the critical role of the middleware components in the proposed framework [27, 29].

Hybrid Enterprise System Architecture:

Integration of Oracle Ecosystem with Cloud Analytics. The final domain of literature covers the integration of traditional enterprise platforms with modern cloud analytics tools, specifically focusing on the Oracle ecosystem components.

$$S = a_0 = g(0) = \sum_{i=1}^{t} g(i) \prod_{j=1, j \neq i}^{t} \frac{-j}{(i-j)} \pmod p \qquad \text{Eq (2)}$$

Role of Oracle REST Data Services (ORDS)

Oracle REST Data Services (ORDS) serves as the crucial middle-tier application that bridges HTTPS requests from web clients to the Oracle Database [30, 31]. ORDS provides: RESTful Web Services: It can expose database tables, views, and, most importantly, PL/SQL stored procedures as secure, high-performance REST APIs [32, 33]. This ability to wrap PL/SQL logic as an RPC (Remote Procedure Call) endpoint is essential for orchestrating the sentiment check.

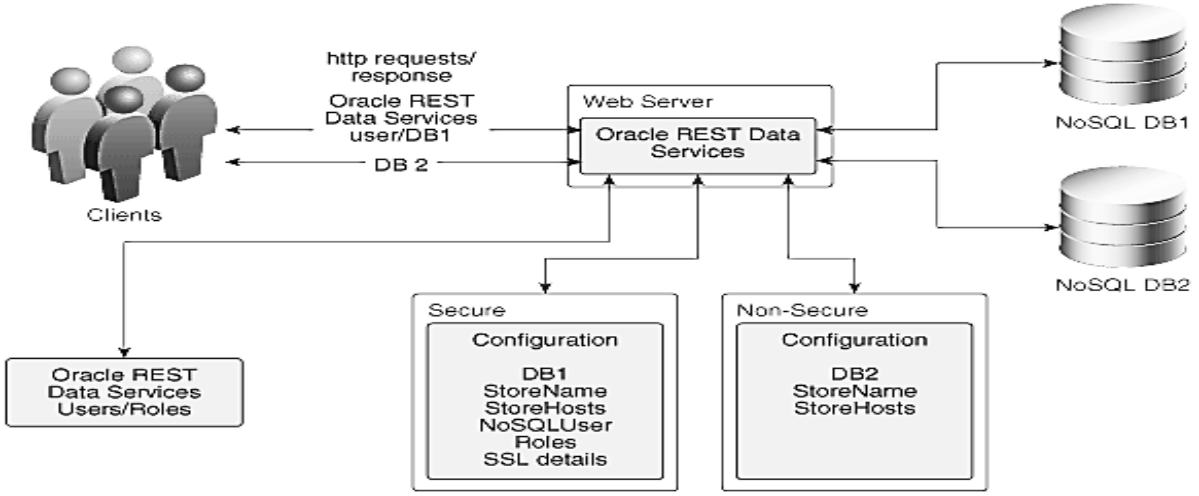

Figure 2.
Typical Environment of Customer Sentiment Aware Using Role of Oracle REST Data Services (ORDS) [34]

Application Gateway: ORDS acts as the gateway for Oracle APEX applications, providing connectivity and security [34]. The literature confirms ORDS's capability to act as a secure, fast conduit for database operations, making it an ideal choice for the low-latency API layer necessary for real-time inference calls.

Oracle APEX for Rapid Application Development (RAD)

Oracle APEX (Application Express) is a low-code development platform for building scalable, secure web applications, built entirely on the Oracle Database [35]. Its key advantage is its proximity to the data, ensuring high performance for transactional and reporting applications. The literature supports the use of APEX for consuming external data and services via RESTful integration [36, 37]. In this research, APEX will serve as the presentation layer, relying on its ability to send the search query to the ORDS endpoints, receive the resulting sentiment classification, and then execute a final search query whose ranking logic is informed by that classification [38].

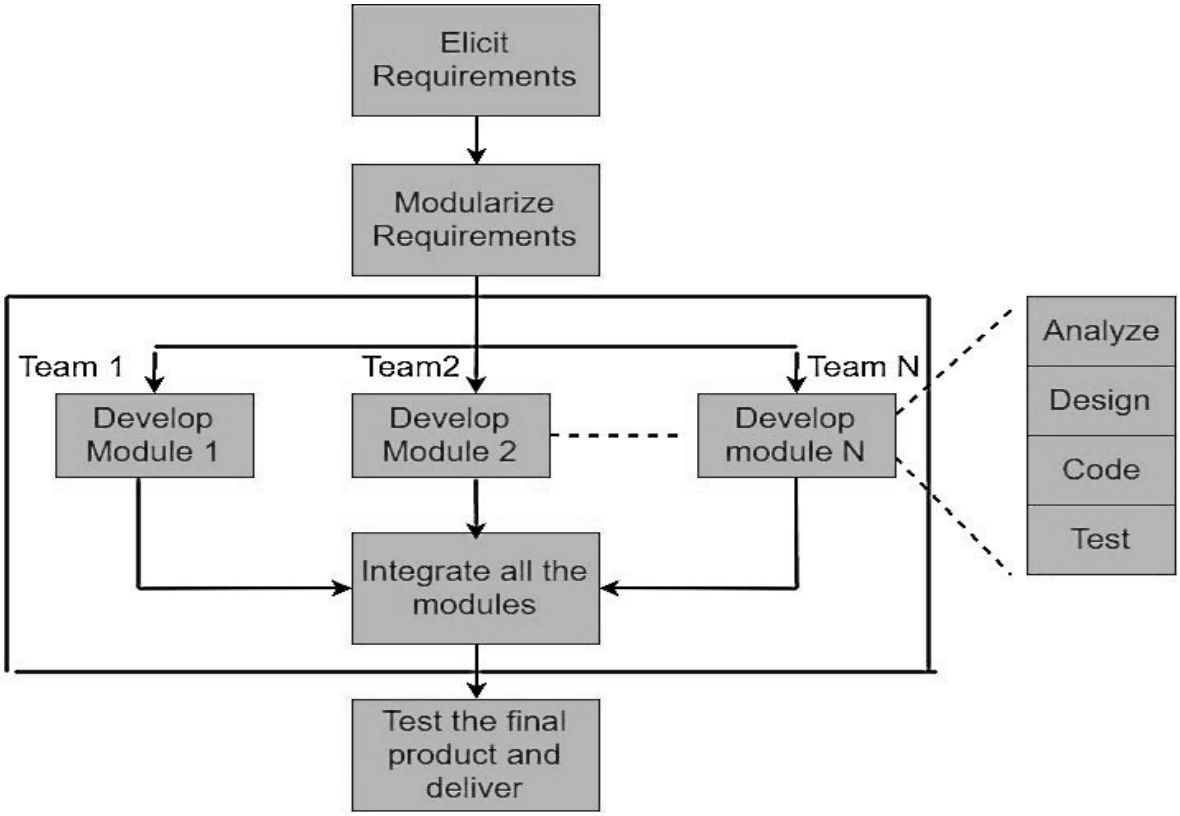

Figure 3.
Generic Process of Oracle APEX for Rapid Application Development (RAD) [39]

Oracle-Databricks Integration Patterns

Oracle to Databricks data transfer in analytic applications is a common issue in the field. The common approaches in this regard include the use of a batch ETL or a change data capture tool in the case of near real-time updates [40, 41]. The current body of research has a major emphasis on Oracle to Databricks data transfer in offline analytics. The gap filled by this thesis is the real-time synchronous round trip from the Oracle APEX/ORDS environment that originates a single live query to the implemented Databricks ML service and returns from it the classification result within milliseconds to satisfy the request of the user. This new kind of hybrid operational method is the main architectural achievement of this research [42].

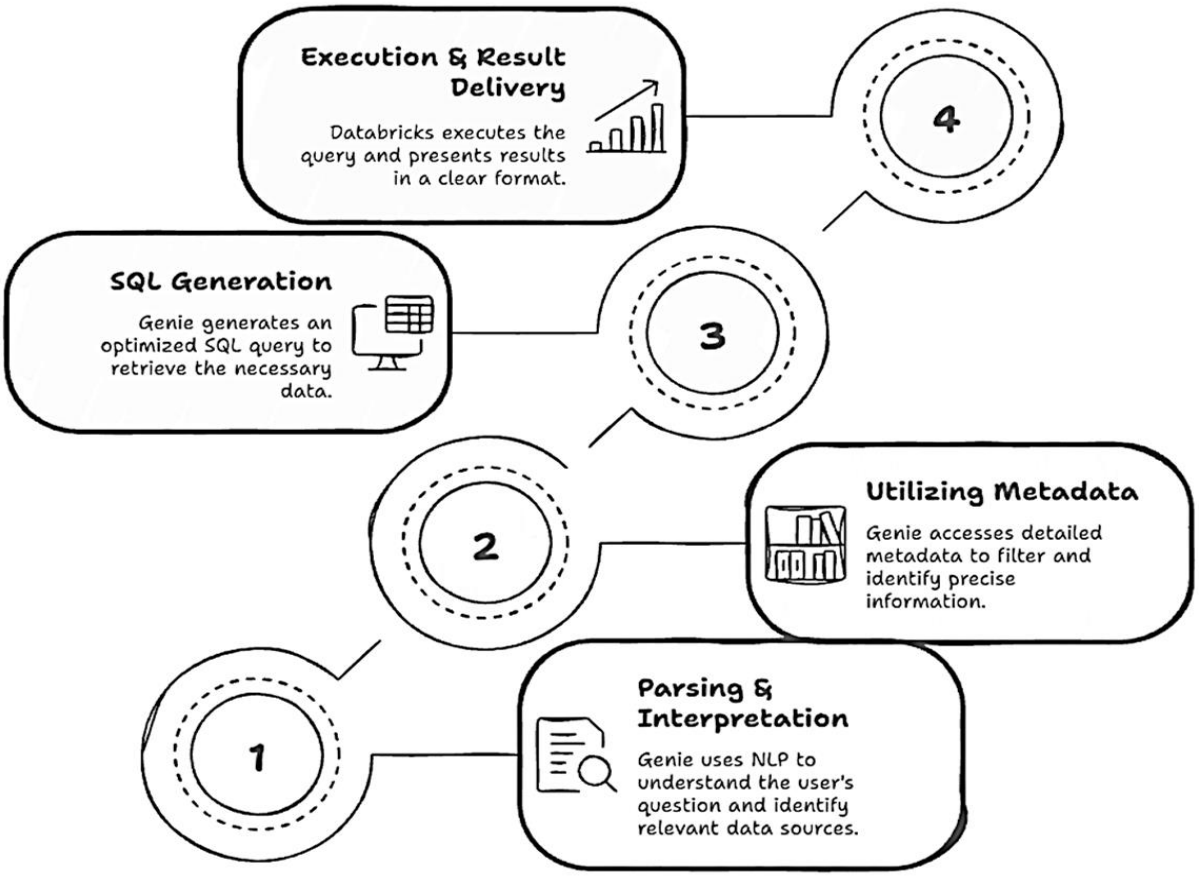

Figure 4.
Generic Process to Boost Your Data Strategy with Databricks [43]

Research Synthesis and Proposed Contribution

Existing literature validates the individual components: sentiment analysis is feasible using ML, Databricks is a scalable platform, and ORDS/APEX form a powerful application stack. This article contributes by integrating these validated, disparate components into a cohesive, operational framework for sentiment-aware search: Novel Real-Time Architecture: Designing and validating the synchronous API handshake between APEX (user interface), ORDS (API gateway), and the Databricks ML Service (inference engine) [44]. Proof of Concept: Delivering a working, end-to-end framework that dynamically alters search result ranking based on query sentiment—a functionality not comprehensively demonstrated across this specific high-performance, enterprise-grade technology stack (Databricks + ORDS + APEX) [45]. This framework will serve as a practical model for implementing MLOps strategies where intelligent features must be seamlessly embedded into existing, low-latency transactional enterprise applications. Sentiment analysis is referred to as a system where a statement is segmented into tiny segments, where learning is made on how they speak (as such, what they do) to each other. Opinion Mining (OM) is the analysis of human behavior based on their textual content. The Internet has gained rapid penetration into the lives of individuals, making the consumption of goods online more popular. Its emergence and ubiquitous nature can provide new means of communication between customers and the service providers [46, 49]. Consumers would prefer to review their consumption experiences using e-commerce websites and their opinions on any given product or service, following the consumption behavior. The sheer volume of online reviews that are developed on review sites,

forums, blogs, etc., can be thought of as a big data problem to the consumers and organizations themselves, in the event that they do not analyze and utilize them in the best way possible. This problem of data overload can be addressed with cognitive computing in this way of processing this multimodal data, as well as converting the raw data into useful information. Cognitive computing has gained more attention in recent times because of its ability to provide an interdisciplinary framework and a collection of technologies to process big data, achieving intelligent thinking processes by reducing the complexity of big data that would otherwise complicate human decision-making [50, 54].

$$Q^{(i)} = \{Q(x_j^{(i)})\}_{j=1}^{m_i},$$

Eq (3)

Early sentiment mining could be interpreted with clearly defined feature weights and decision rules that the applied practitioner could utilize to read the predictions as a result of being determined by a specific linguistic pattern. However, they were unable to do the broad cross-domain and fine-grained context generalization because they relied on hand-crafted characteristics. CNNs, RNNs, and LSTMs were more precise and less comparable. The progressions made it easier to act on complex subjective issues, but the representations obtained became less transparent, and personal predictions were difficult to explain [55, 56]. The pretraining paradigm and transformer architecture constituted a text classification and subjective task general-purpose framework. BERT proposed bidirectional and contextualised representations by masked language modelling and GPT showed the strength of autoregressive language modelling. It was found that the self-attention mechanism also allowed long-range dependencies to be modeled without the vanishing gradient issues of RNNs, and this achieved huge performance gains across benchmarks [57, 58].

Large-scale, instruction-tuning, and few-shot learning Large language models (LLMs) such as GPT-3 [59], PaLM [60], LLaMA [61], and GPT-4 [62] expanded the abilities of large scale, instruction tuning, and few-shot learning. Subjective zero-shot and few-shot results with no task-specific fine-tuning of these models are radically altering our thinking when using NLP applications.

At the same time, explainable NLP has come to include feature-attribution and saliency-type tools (e.g., LIME [63], Integrated Gradients [64], SHAP [65]) to rationalization, with the explanations being in natural language in terms of extracting the spans of evidence or generating justifications [66]. The feature-attribution techniques focus on influential input tokens, are gradient-based or perturbation-based, but require technical skills to interpret and can not be explained with natural language [67]. Rationalization manages these deficiencies by producing human-readable textual explanations that can be understood by the non-expert users [68].

$$G_B = \sum_{i=1}^{N} W_i \cdot G_{L_i}$$

Eq (4)

Cognitive technologies, such as big data, cloud computing, artificial intelligence, machine learning, pattern recognition, data mining and natural language processing, are assisted by the cognitive computing systems in carrying out the cognitive work of observation, interpretation, assessment, and decision-making,

which human brain does. Overall, cognitive computing attracts general interdisciplinary theories, techniques and tools to model human cognition, which propels cognitive systems and is capable of perceiving, reasoning, learning and acting autonomously and, thus, offering actual human-machine collaboration [69, 70].

$$fd_k(x) = \frac{1}{n}\sum_{i}^{n_m} l(p_i, q_i; x) \quad \text{Eq (5)}$$

Two broad categories of rationalization, in which it selects critical terms or phrases of the input as the rationale and abstractive rationalization, in which it produces new explanatory text summarizing the reasoning, are identified. The existing LLMs accommodate one of these options and allow them to produce natural language and prompt them to provide a set of justifications through chain-of-thought processes. All audience of non-expert people are more attracted to rationalization, which is used to explain the arguments in writing form, unlike numerical attributions, which makes AI systems easier to understand and accept. This is particularly important in subjective tasks during which context, tone and implicit meaning play an important role in human perception [71, 72].

Sentiment orientation, which is the outcome of the sentiment classification, has been a significant source of reference and has been an influencer not only to persons but also to organizations during the decision-making process. The sentiment polarity of the user reviews has been seen to be one of the most useful determinants which makes the user reviews helpful in the aspect of making a purchase decision and customers have the intuition to make a purchase of a product that is reviewed as positive [73, 74]. On the other hand, basing its marketing strategy on the sentiment orientation of the reviews left by the consumers, the organization can adjust its brand positioning, introduce marketing messages, develop new products and other processes to improve the organizational performance. As a result, the quality of the sentiment classification is the direct measure of whether consumers and organizations can make smart or not based on the reviews and poor results can lead to ineffective or even wrong decisions [75, 76].

Natural language processing (NLP) and Natural Language Generation (NLG)

One such area of cognitive computing that is very important is natural language processing (NLP); this gives provision to a continuous learning process in which cognition systems can be applied to make sound data-driven decisions. The processing of unstructured data in a context where questions are asked and providing intelligent cognitive responses i.e., allowing machines to communicate with humans, is one of the simplest task in the cognitive computing processes. This is what NLP can do best, i.e., to transform an unstructured material to a knowledge base in the form of a cognitive construct which defines the meaning of natural language [77].

$$minimum fd_k(x) = \sum_{m=1}^{C*M} \frac{1}{n} fd_m(x) \quad \text{Eq (6)}$$

Natural Language Generation (NLG) refers to the procedure of giving out phrases, sentences and paragraphs that are meaningful based on an internal representation. It is an aspect of Natural Language Processing and occurs through four stages which

are: identifying the goals, planning on how the goals could be accomplished by considering the situation and available communicative resources and implementing the plans as a text . It entails several steps, such as content determination, text planning, sentence structuring, and linguistic realization, shifting to more human-like output based on the more advanced deep learning models [78]. Transformers and LLM systems are state-of-the-art but act as black boxes, thus it is hard to know why a subjective prediction was generated (e.g. irony vs literal, positive vs. negative). Opacity compromises trust, auditability and safety in sensitive fields like healthcare, legal decision-making, content moderation and financial analysis. To determine reliability and determine the possible bias or errors, users and stakeholders require to know not only what the model predicted, but also how and why the prediction was made [79].

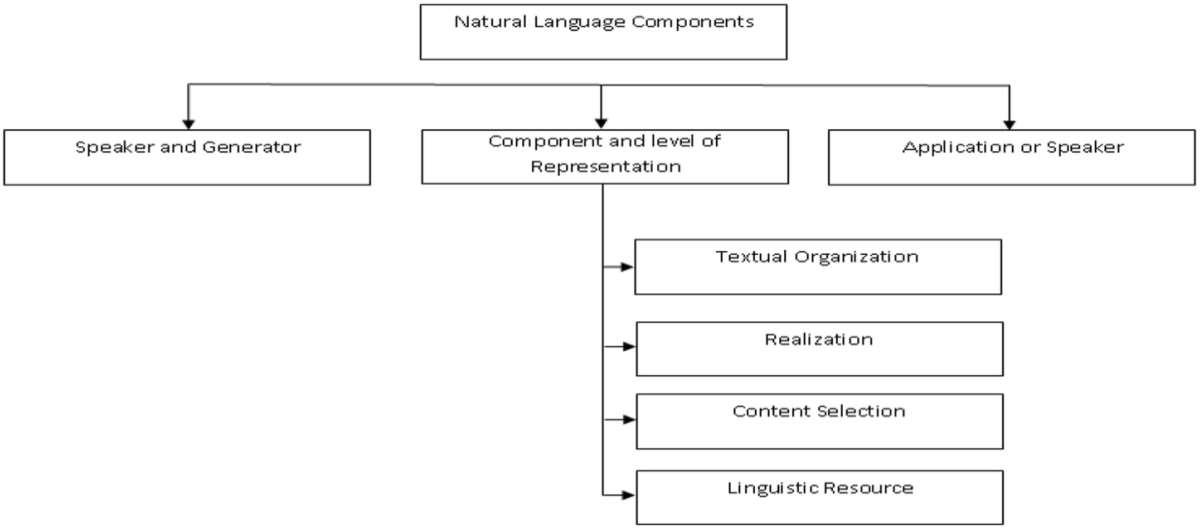

Figure 5.
Major Components of NLG and NLP [80]

Meanwhile, subjective tasks are generally vague and specific to the situation (sarcasm, humor, aesthetics), which usually leads to a difference between the annotators and the difficulty of assessment. The sarcasm, like, can be detected through reading each other and mutual cultural background, the tone of voice, or situational information that is not present in the text itself [80]. The discrepancy, surprise, subjective appreciation is what the humor recognition is concerning, unlike people and cultures. Emotion recognition must also settle the multidimensional affective conditions, which may imply a combination of various emotions, or the outcry of culturally-specific emotional categories [81]. These high-performance and low-transparency demands coexist, hence explaining the existence of a single approach to subjectivity, and the reason why the process of rationalization is needed to demonstrate how the judgment was arrived at in a precise manner [82, 83]. The field must also provide predictively accurate methods, give meaningful explanations where users trust and are appropriate to depend on model outputs [84]. This paper uses four sources of quality and the basis applied to cite them: Sentiment analysis methods and datasets: classical methods of machine learning, deep learning, and transformers, popular datasets such as IMDb, Sentiment140, Twitter US Airline, and SemEval shared tasks [85, 86]. Machine learning. They can be applied to do numerous linguistic analyses i.e. lexical analysis, syntactical analysis, discourse analysis etc. NLP can therefore be used to automate the thinking process of acquiring the meaning of words, recognition of patterns and association between words and providing layers of context perception. Some of the NLP-based applications that have been unveiled

within the context of cognitive computing would include the possibility to understand the word-of-mouth (WOM) of the text-based comments left by the customers in the online web, under the guidance of sentiment analysis, to discover the true emotions or attitudes by the customers towards any product or service. Sentiment analysis, sentiment classification or opinion mining is a binary classification problem of determining the textual reviews as being of one of the two polarity types of positive and negative [88, 89].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_1 - \bar{Y})^2} \qquad \text{Eq (7)}$$

The use of NLP is based on statistical applications, and other techniques, such as Text classification with transformers: architecture and overview of the BERT-family encoders, GPT-family decoders, and adaptations of the classification tasks, efficiency and safety issues [85]. Subjective language LM: vast sentiment, emotion, sarcasm, humor, stance, metaphor, intent, and aesthetics with zero-shot and few-shot evaluation [90].

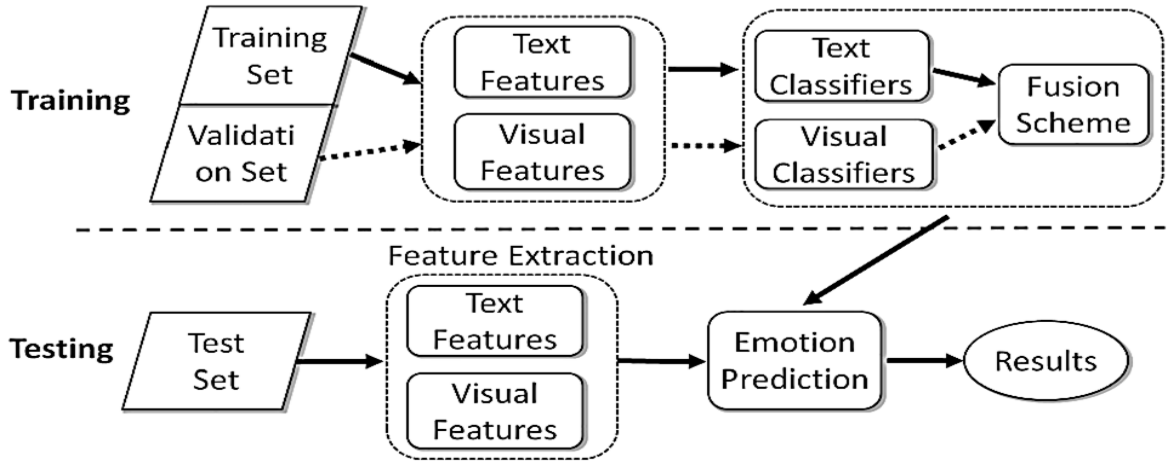

Figure 6.
Analysis of NLP queries dataset Testing and Training [87]

Table 1.
Analysis of Textual data Model

Ref	Model	Task	Performance
[91]	Dynamic convolutional neural network (DCNN)	Binary sentiment prediction	The accuracy of binary sentiment classification is 86.8%
[92]	Deep recursive neural network (DRNN)	Multi-class sentiment prediction	The accuracy of fine-grained sentiment classification is 48.5%
[93]	Uniform-layer LSTM architecture	Twitter sentiment prediction	The accuracy of six-way question classification is 93.0%
[94]	Uniform-layer LSTM architecture	Sentence-level sentiment classification	Uniform-layer model achieves average 0.8%
[95]	Coupled-layer LSTM architecture	Classification	improvement of the performances
[96]	Shared-layer LSTM architecture	Document-level sentiment classification	Coupled-layer model achieves

Transformer and LLM systems can be used to give state-of-the-art results, but are opaque black boxes, so it is harder to reason why a subjective prediction was made (e.g., irony vs. literal, positive vs. negative). In sensitive sectors, including healthcare, legal decision-making, content moderation, financial analysis, and so on,

transparency threatens trust, auditability, and safety. Users and stakeholders should not only know what the model predicted, and why it specifically did that, but also to determine how reliable the prediction is, and any possible biases or errors [97].

Meanwhile, subjective assignments are apt to be ambiguous and circumstantial (sarcasm, humor, aesthetics), and usually lead to the difference between the annotators and problems with assessment. Sarcasm can be detected, like, depending upon mutual cultural context, tone of voice or situational knowledge that is not available in the text itself [98]. The incongruity, surprise and subjective appreciation humor recognition is incongruent to individuals and cultures. The multidimensional affective conditions that emotion recognition has to negotiate can be either a combination of various emotions or an expression of culturally-specific categories of emotions [99]. High-performance and low-transparency requirements in both directions simultaneously result in an impetus to choose a single approach to subjectivity and explain the possibility of fine judgments and the process of rationalization to demonstrate the logic behind the judgment in a correct manner [100]. The field must provide predictively correct methods, present meaningful explanations that make the users trust and right to trust the model output.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \qquad \text{Eq (8)}$$

The paper has integrated four sources of quality and the underpinnings of the citation of the same: Sentiment analysis approaches and datasets: classical approaches to machine learning, deep learning, and transformers, with standard datasets including IMDb, Sentiment140, Twitter US Airline, and SemEval shared tasks [101, 102]. Transformer-based text classification: architectural description and summary of the BERT-family encoders and GPT-family decoders along with their adaptations to the classification task, their efficiency, and safety issues [103]. Subjective language Llamas: large-scale taxonomy of sentiment, emotion, sarcasm, humor, stance, metaphor, intent, and aesthetics [104].

Table 2.
Major Datasets for Sentiment Analysis

Dataset	Size	Domain	Classes	Ref
IMDb Movie Reviews	50,000	Movies	Binary (pos/neg)	[105]
Sentiment140	1.6M	Twitter	Binary (pos/neg)	[106]
Twitter US Airline	~14,000	Customer service	3-class (pos/neu/neg)	[107]
SemEval-2017 Task 4	Varied	Twitter	Multi-task	[108]
Amazon Product Reviews	Millions	E-commerce	5-star scale	[109]
Yelp Reviews	1.6M+	Restaurant/business	5-star scale	[110]

Explainable NLP through rationalization, extractive and abstractive mechanisms, schemes of evaluation that are based on fidelity and plausibility and human based means of evaluation. It is aimed at standardizing task taxonomies, model families, datasets/benchmarks, and explainability strategies, rigorously on the said materials, to be handy in assisting trace scholarly research and high density IEEE referencing. Such a combination will provide the researchers and practitioners with the entire picture and learn more about the real situation in the area of subjective NLP and explainability, along with gaps and the way to conduct further research. Coherency of subjectivity vision + elucidability. We convert sentiment analysis (to interpretable ML to DL to transformers/LLMs), subjective task taxonomies, and explainability systems into a single system, justifying it as one of the first-class subjective NLP components [111, 112]. The integration identifies the inherent synergy in subjective language

understanding which entails the need to have contextual and practical reasoning and the generation of explanations which also require these types of reasoning capacity. The unified taxonomical classification of subjective work. We are adopting an eight-viewpoint perspective sentiment, emotion, sarcasm, humor, stance, metaphor, intent, aesthetics, which is congruent with the present surveys in the age of the LLM [113, 114].

Table 3.
Major Datasets for Emotion Recognition

Dataset	Iteration	Size	Emotions	Domain	Ref
ISEAR	IT (1)	~7,600	7 basic	Surveys	[115]
GoEmotions	IT (2)	58,000	27 fine-grained	Reddit	[116]
SemEval-2018 Task 1	IT (3)	~10,000	11 emotions	Twitter	[117]
DailyDialog	IT (4)	13,000	7 basic	Dialog	[118]
MELD	IT (5)	13,000	7 basic	Multimodal TV	[119]

LITERATURE REVIEW

Sentiment analysis is performed in two categories, in general. One of them is the machine learning-based methods and the other is lexicon-based methods. The latter is at a disadvantage that the approach based on machine learning is highly regarded in academia and in the industrial world since the former frequently outperforms it better. Deep learning is a machine learning algorithm and it has been effective because of enhanced power of chip processors, lower hardware costs and also contributed to enhanced machine learning algorithms [120]. Accurate sentiment analysis in e-commerce, according to multiple studies, new machine learning techniques are proposed or advance the existing algorithms, implying to report a higher level of accuracy due to the use of powerful algorithms to the feature extraction [121].

The related ones are subjectivity, sentiment, and explainability, with the former being the least explainable or the imprecise, and the latter is the imprecise and most explainable, which is natural. Spread that subjectivity, sentiment and explainability are related to each other in the following way; the less explainable, the more imprecise the subjectivity, and the less explainable but imprecise, sentiment. The point of intersecting subjectivity and explainability is that they are both concerned with interpretation. The reasoning behind the subjective task sentiment analysis was based upon decipherable lexicons and feature weights which indicated decision logic. The Bag-of-words and TF-IDF representations made it possible for the practitioners to have a view of the words that were either associated with positive or negative labels and this naturally provided transparency [122, 123]. This remaining invisible stimulated rationalizations and attention-visualization methods to restore transparency [124, 125]. Subjective NLP is enhanced in two ways by explainability:

Ambiguity clarifying: The difference between sarcasm and real praise, the recognition of emotion stimuli or the revelation of metaphorical mappings with referencing to contextual cues [126, 127]. This can be promoted by facilitating users to verify the validity of textual evidence in furthering model predictions particularly in affective systems that are deployed to mental health, customer service and content moderation. Thus, rationalization is not a marginal issue, but it is actually a component of the modeling of human-like subjectivity. Deep learning or deep neural networks (DNNs) is a sub-specialty of machine learning algorithms that has widely applied to traditional fields of machine learning such as computer vision, speech recognition and

natural language processing [128]. The state of the art can be achieved in deep learning when applied to sentiment analysis which is also among the most popular problems in NLP, as it can learn the representations of the data with an extremely high level of abstraction using the computational models composed of many processing layers [129].

$$\mathrm{TDI} = \sqrt{(\Delta C)^2 + (\Delta \sigma)^2} \qquad \text{Eq (9)}$$

Because of this sentiment analysis is being performed more and more by researchers on the basis of deep learning. Some of the effective network architectures used in deep learning include convolutional neural network (CNN), recursive neural network (RNN), recurrent neural network (RNN) and deep belief network (DBN), among others. In general, the current research on the subject matter has two directions. Other works concern the building of efficient network encompasses on straightforward deep learning models to solve diverse issues in sentiment analysis tasks [130, 131], but others assume comparative studies of the varying simple deep neural networks on a specific challenge to provide effective recommendations in the selection of deep learning models [132, 133]. In this section, the brief description of some of the representative research methods on sentiment analysis using deep learning methods is outlined. The dynamic convolutional neural network (DCNN) refers to a CNN network, which is employed to semantically model a sentence whenever performing a sentiment mining task. The network takes into account the length of the input sentences and expressly records the word relations of varying sizes by creating a feature graph over the sentence. It is also the case that the network is highly efficient in an array of sentiment analysis tasks. In [134], three types of information sharing architecture were proposed including uniform-layer architecture, coupled-layer architecture and shared-layer architecture.

$$\mathrm{MCC} = \frac{\mathrm{TP} * \mathrm{TN} - \mathrm{FP} * \mathrm{FN})}{\sqrt{((\mathrm{TP} + \mathrm{FP}) * (\mathrm{TP} + \mathrm{FN}) * (\mathrm{TN} + \mathrm{FP}) * (\mathrm{TN} + \mathrm{FN}))}} \qquad \text{Eq (10)}$$

They have included an RNN as a part of a multi-learning system to project arbitrary text straight to semantic expressions in the shape of vectors with task-specific and shared layers and they have demonstrated that their models can be utilized to enhance the efficiency of a classification task by the presence of other related tasks. As a means to allow the potential of the capacity of a hierarchical representation, [135] suggested a deep recursive neural network (deep RNN) with a stack of recursive layers. They tested the network using the fine-grained sentiment classification and the result of the experiment showed their approach was superior to the previous ones in the sentiment analysis task. The semi-supervised recursive autoencoders (RAE) of [136] learns to learn the representations of the multi-word phrases in the form of vectors. The model can better solve sentiment prediction tasks compared to other state-of-the-art algorithms, and solve sentence-level sentiment distribution compared to several baselines. [137] proposed a VBN framework of learning word dependencies in text, which has a fixed number of variables. They trained time-delayed network with the deep DBN network to obtain the initial weights of the neurons in the hidden layer, and trained the dynamic Gaussian Bayesian networks.

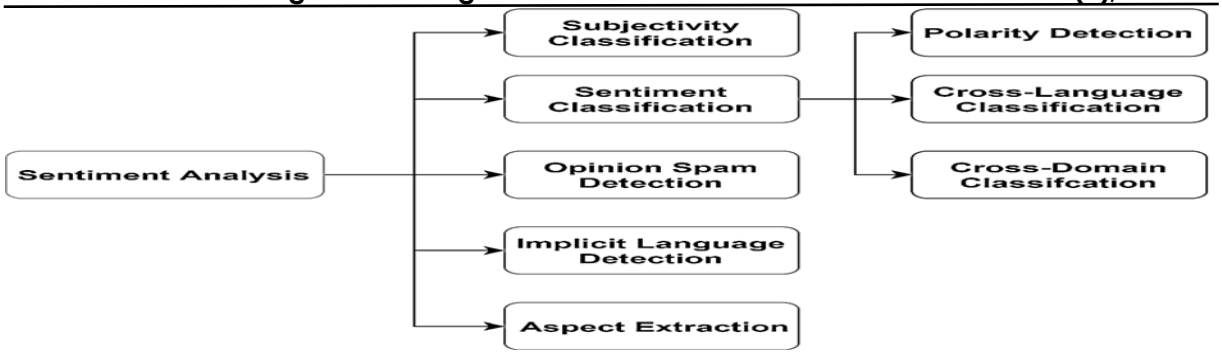

Figure 7.
Tasks of Generalized Sentiment analysis Approach [138]

Experimental results indicated that VBN is capable of greater than 30 per cent improvement over state of the art baselines. Research on four contrasting types of features, which are the language category features, review metadata, readability and subjectivity, which result in the quality of the online reviews, and proposed a new predictive model of review helpfulness using them. Three machine learning algorithms (Naive bayes, Support vector machine and random forest) were used to formulate the prediction model. It was found out that the proposed model could give a predictive accuracy of over 77 percent to actual review data, and a combination of attributes can give the highest predictive score. It was also apparent that these aspects may be potent predictors of the quality of the review. Other studies also examine the characteristics of reviews that are related to the reviewer to compare the usefulness of reviews [139].

The article by [143] stood out of the other papers that utilized the signaling theory to develop an elaborate model of the exploration of the variables that influence the quality and usefulness of the review. About the theoretical backgrounds of the signaling theory, they identified two types of signals, i.e., content-related signals of reviews (specific content and writing style), and reviewer-related signals (reviewer knowledge and non-anonymity) in order to make attempts at modeling the interrelations between them and the review helpfulness. Based on the suggested model, the Tobit regression analysis showed that the reasons behind the improved quality review were more signals associated with the quality of the product, stronger signaled strength of the sentiment polarity in the reviews, lower level of signaled uncertainty and high level of signaled expertise that could better explain the helpfulness of the reviews and make more accurate predictions on most helpful reviews than the results of the previous review predictions [144, 145]. They determined the nature of attributes of a review that could lead to a high-quality or the most useful review. In forming textual qualities of reviews to measure the quality of the reviews and in analyzing their impact on the genre of sentiment classification, their contribution to the issue is very informative and descriptive to our study.

METHOD AND MAJOR DATASETS ANALYSIS

The literature search and selection were done by searching high-quality research papers from journals like IEEE Access, Frontiers in Artificial Intelligence, Applied Sciences, MDPI, Springer and arXiv preprint awaiting publication. The present survey is a synthesis of the results of four high-quality and extensive surveys that have been published since 2023-2025: A total of 150 references are quoted in these four sources, which represent a comprehensive overview of the discipline, including the beginnings and the latest advancements in the field.

Detection Methods

Semantic violation of selection preference, conceptual metaphor theory, Word embeddings represent abstract-concrete mappings, Neural: BiLSTM using contextualized representation and Transformers: BERT learns metaphorical patterns of use. Understanding the goal/purpose of communication which was behind the utterance of a user. Examples: Book me a flight to Toronto is an expressive of an intent to book a flight. Fine-grained intent taxonomies (100 more intents in banking/retail), Out-of-scope. utterance handling, Domain adaptation, and Multilingual intent classification.

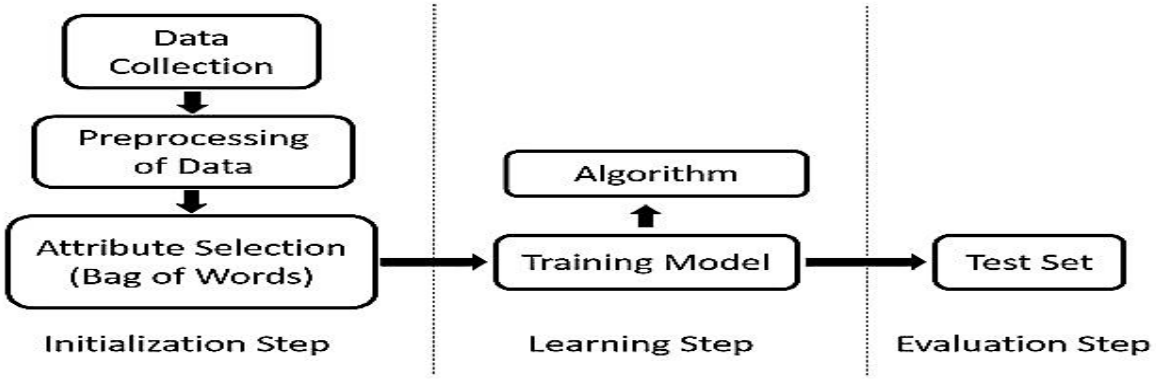

Figure 8.
Training and Testing Approach

LEVELS OF SENTIMENT ANALYSIS

In this survey, we trace the history of paradigms of subjective NLP models and discuss their implications in regard to explainability. Tokenization & normalization includes Lowercasing, punctuation and stop-word filtering, Lexical: TF-IDF, n-grams (unigrams, bigrams, trigrams), Sentiment: MPQA, SentiWordNet, AFINN, NRC Emotion Lexicon, Linguistic: POS tags, dependency relations, negation processing Naive Bayes Probabilistic, fast, interpretable, feature independence, Support Vector Machines Kernel methods for non-linear boundaries; strong baselines, Logistic Regression [154] Linear model with probability outputs; interpretable coefficients, Performance: Accuracy on sentiment analysis benchmarks 75-85%, Explainability: Have a higher transparency by feature weights and lexicon scores [155]. Manual feature engineering work, Low generalization between domains, does not process figurative language and context well.

COMPARATIVE ANALYSIS AND INTEGRATION

Cross-Task Patterns and Explainability Trade-offs Across Model Families

Analyzing performance across the eight subjective tasks reveals consistent patterns

Table 15.
Model Performance Summary Across Tasks

Task	Classical ML	Deep Learning	Transformers	LLMs (Zero-shot)	LLMs (Few-shot)
Sentiment Analysis	75-85%	85-92%	92-96%	85-95%	90-97%
Emotion Recognition	70-80%	80-88%	88-93%	70-85%	80-90%
Sarcasm Detection	60-70%	70-80%	80-88%	60-75%	70-82%
Humor Detection	55-65%	65-75%	75-85%	65-80%	72-85%
Stance Detection	65-75%	75-83%	83-90%	75-88%	82-92%

Task	Classical ML	Deep Learning	Transformers	LLMs (Zero-shot)	LLMs (Few-shot)
Metaphor Recognition	60-72%	72-82%	82-90%	70-85%	78-90%
Intent Detection	80-88%	88-93%	93-97%	80-92%	88-95%
Aesthetics Assessment	50-60%	60-70%	70-82%	65-78%	70-83%

Table 16.
Explainability Characteristics by Model Family

Model Family	Accuracy	Inherent Interpretability	Post-hoc Explainability	Rationalization Support
Classical ML	Low-Medium	High (feature weights)	Low need	Lexicon-based
Deep Neural	Medium	Low (hidden states)	Medium (attention)	Attention-based
Transformers	High	Low (distributed)	Medium (attribution)	Extractive modules
LLMs	High	Very Low (scale)	High (generation)	Abstractive prompting

CONCLUSION

Integration of LLM abilities, rationalization and strict assessment standards sets the field to achieve such a vision. Future research should give more importance to standardized benchmarks, causal explainability, multimodal reasoning, and human. Feedback, multiculturalism, computational performance, and ethics governance. By integrating subjective language understanding with explainability, we enable The solution to integrating predictive models into Oracle Application Express (APEX) applications can be found through the use of Oracle machine learning (OML4SQL) to perform in-database processing and using the REST API to integrate external models. The methodology presented feasible procedures of creating, testing and implementing machine learning models in the Oracle ecosystem and provided code samples illustrating both strategies. Using the low-code development of the APEX and the powerful in-database analytics of OML, developers can create intelligent and data-driven applications and provide high performance and security with real-time insights. The importance of such integration is that it helps to democratize advanced analytics to allow organizations to optimize the efficiency of their decisions and operations in numerous fields, such as retail, finance, and healthcare.

The in-database model based on OML4SQL is especially beneficial to the applications that need low latency and high level of data security. OML4SQL reduces data movement and thus lowers latency by processing data in Oracle Database, as well as adhering to regulations, including GDPR and CCPA. This can be very useful in applications that require real time predictions, particularly in the enterprise sector like inventory forecasting or fraud detection. The declarative interface of APEX also makes it easy to create a user-friendly interface and allows predictive analytics to be used by non-technical users, such as business analysts and citizen developer. Such correspondence with the low-code philosophy is enabling organizations to quickly develop smart applications without the need to have a lot of programming skills. The other REST API-based solution is more flexible in the case of scenarios that demand sophisticated algorithms, e.g., deep learning models [24]. With the addition of external frameworks, including scikit-learn or TensorFlow, developers can support more complicated use cases, such as image analysis and natural language processing, that OML4SQL currently does not support [12]. Nonetheless, this solution brings in a few challenges, including the network latency and other security considerations, which are supposed to be well managed, to create a strong performance. This dual

approach used in the methodology, i.e., in-database and external integration, gives the developers the option to select the optimal approach to use depending on their particular need, considering the performance and scalability of performance and algorithmic requirements. Regardless of these advantages, there are still challenges like data quality, the interpretability of the models, and limitations of the algorithms, as outlined in the previous sections. These can only be handled by a strong data preprocessing, powerful explainability tools and possible extensions of the algorithm library of OML [19]. To address these constraints and improve the effectiveness of the integration, the proposed future recommendations offered solutions that can be implemented, such as automated retraining pipelines, integration with OCI AI services, and no-code OML interfaces. Such developments would help to optimize the development process and expand the availability of machine learning in the Oracle ecosystem.

The integration has further implications that go beyond technical implementation. Organizations can enhance innovation, streamline operations, and provide individual user experiences by adding predictive functionality to APEX applications. The applications show why a combination of low-code development and machine learning has the potential to be transformative and allow organizations to remain relevant in a data-driven world.

With the development of low-code platforms, machine learning integration with APEX will become the key to the future of enterprise applications. The suggestions to integrate complex algorithms, enhance the level of explainability, and use the AI services offered by clouds are the guiding steps towards improvements in this integration. Oracle can support developers and organizations to develop scalable, intelligent applications that can create business value by overcoming existing constraints and adjusting to the new trends. The article is an asset to a practitioner that would like to apply predictive analytics to the Oracle ecosystem, as the article provides a practical guide with a vision of future developments. The bottom line is that the low-code functionality combined with machine learning is the potential of APEX that allows organizations to embrace the power of data-driven insights, which in turn leads to innovation and efficiency in industries.machines not only to predict what humans feel or intend but also to explain why.

Transparently, responsibly, and across cultures. This single framework drives forward science. Knowledge and skills in the practical implementation of NLP systems, which can be used by human beings to serve their needs. Creditworthiness and responsibility. The contemporary healthcare system produces enormous amounts of data from various sources. They are electronic health records (EHRs), medical imaging systems, lab results, wearable health monitors, mobile health apps, insurance claims and, most recently, genomics data. It is this heterogeneous combination of structured and unstructured data, which encompasses the patient demographics and diagnostic codes, but goes all the way up to the continuous biometric streams to what is known as big data in healthcare. Big data presents radical possibilities in medicine. It allows making diagnoses more accurately, supporting predictive analytics, providing patients with an opportunity to detect diseases at an early stage, managing the health of the population, and improving clinical decision-making.

Nevertheless, storing and controlling such large volumes of sensitive data is extremely demanding in terms of technical and ethical factors. The healthcare system's big data lifecycle can be generally broken down into five steps that are essential: data collection, storage, analysis, utilization, and destruction. There are vulnerabilities

presented by each stage. As an example, when collecting data, the data sent by IoT-based devices, such as fitness trackers or smart medical sensors, may be compromised because of the insecure transmission protocols. As soon as they have been gathered, the information is stored in centralized or cloud-based repositories that are frequently targeted by cybercriminals because of the high price of medical records.

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Consent to Participate: Yes
Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

REFERENCES

A. Ali, M. A. H. Farquad, C. Atheeq, and C. Altaf, "A Quantum Encryption Algorithm based on the Rail Fence Mechanism to Provide Data Integrity", Eng. Technol. Appl. Sci. Res., vol. 14, no. 6, pp. 18818–18823, Dec. 2024.

A. Atanasova, J. G. Simonsen, C. Lioma, and I. Augenstein, "Generating label cohesive and well-formed adversarial claims," in Proc. EMNLP, 2020, pp. 3168–3177.

A. Chowdhery, S. Narang, J. Devlin, M. Bosma, G. Mishra, A. Roberts, P. Barham, H. W. Chung, C. Sutton, S. Gehrmann, et al., "PaLM: Scaling language modeling with pathways," arXiv preprint arXiv:2204.02311, 2022.

A. Go, R. Bhayani, and L. Huang, "Twitter sentiment classification using distant supervision," Tech. Rep. CS224N Project Report, Stanford University, 2009.

A. L. Buczak and E. Guven, "A survey of data mining and MLfor cybersecurity," IEEE Commun. Surveys Tuts., vol. 18, no. 2, pp. 781–812, Secondquarter 2016. doi: 10.1109/COMST.2015.2454504. (IEEE).

A. Maas, R. E. Daly, P. T. Pham, D. Huang, A. Y. Ng, and C. Potts, "Learning word vectors for sentiment analysis," in Proc. ACL, 2011, pp. 142–150.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, "Attention is all you need," in Advances in Neural Information Processing Systems, vol. 30, 2017.

Abbas, G., Ali, A., Mushtaq, Z., Rehman, A. U., Hussen, S., & Hamam, H. (2025). Advancing wind energy potential estimation through multidistribution wind speed analysis in coastal Pakistan. Scientific Reports, 15(1), 18297.

Abdullah, M. M., Ghafoor, U., Qadeer, Q. B., Khadim, F., Khan, H. S., Ahmad, A., & Khan, H. (2025). An Efficient of Artificial Intelligence based Brain Tumor Diagnosis and Classification: An Advance Medical Diagnosis Approach. The Asian Bulletin of Big Data Management, 5(2), 208-242.

Abdullah, M. M., Khan, H., Farhan, M., & Khadim, F. (2024). An Advance Machine Learning (ML) Approaches for Anomaly Detection based on Network Traffic. Spectrum of engineering sciences, 2(3), 502-527.

Adil, M. U., Ali, S., Haider, A., Javed, M. A., & Khan, H. (2024). An Enhanced Analysis of Social Engineering in Cyber Security Research Challenges, Countermeasures: A Survey. The Asian Bulletin of Big Data Management, 4(4), 321-331.

Ahmad, I., Nasim, F., Khawaja, M. F., Naqvi, S. A. A., & Khan, H. (2025). Enhancing IoT Security and Services based on Generative Artificial Intelligence Techniques: A Systematic Analysis based on Emerging Threats, Challenges and future Directions. Spectrum of engineering sciences, 3(2), 1-25.

Ahmad, J., Salman, W., Amin, M., Ali, Z., & Shokat, S. (2024). A Survey on Enhanced Approaches for Cyber Security Challenges Based on Deep Fake Technology in Computing Networks. Spectrum of Engineering Sciences, 2(4), 133-149.

Akmal, I., Khan, H., Khushnood, A., Zulfiqar, F., & Shahbaz, E. (2024). An Efficient Artificial Intelligence (AI) and Blockchain-Based Security Strategies for Enhancing the Protection of Low-Power IoT Devices in 5G Networks. Spectrum of engineering sciences, 2(3), 528-586.

Alharthi, A. I., Khalid, A., Ahmad, P., Ali, A., Saleem, S., & Munir, M. A. (2025). A study on the role of moderate optical band gap energy in dielectric properties of NiFe 2 O 4 nanoparticles by Ce ion doping for electronic device applications: the effect of doping concentration. Physical Chemistry Chemical Physics, 27(23), 12405-12415.

Ali, A. (2019). Intelligent Auto Traffic Signal Controller for Emergency Vehicle by Using. Journal of Engineering and Applied Sciences, 14(1), 76-82.

Ali, A., Hansen, T. M., Liaquat, S., & Hussain, T. (2025, June). Energy-constrained critical load aware post-disaster home energy management. In 2025 IEEE Kiel PowerTech (pp. 1-6). IEEE.

Ali, Arshad. "Coarse Classification of Terrain Image Information by Using Sobel Edge Detection Technique." International Journal of Computer Network and Information Security 18 (2018): 149-154.

Ali, Arshad. "Coarse Classification of Terrain Image Information by Using Sobel Edge Detection Technique." International Journal of Computer Network and Information Security 18 (2018): 149-154.

Ali, G., Shahbaz, H., Hassan, M. A., Ahmad, M., & Waleed, M. (2024). An Enhanced Approach of Exploring Digital Economy Using Modern Computer Networks. Spectrum of Engineering Sciences, 2(4), 292-312.

Ali, H., Ayub, N., Irfan, A., Fayyaz, S., Masood, H., Ahmad, A., ... & Khan, H. (2025). A Unified AI-powered Social Media Platform for Intelligent Scheduling and Data Driven Analytics Using Multi-Layered Artificial Neural Networks (ANNs): https://doi. org/10.5281/zenodo. 17572988. Annual Methodological Archive Research Review, 3(11), 94-134.

Ali, I., Saleem, M. U., Khan, A. A., Naz, A., Nawaz, M., & Khan, H. (2025). An Enhanced Artificial Intelligence Generated Virtual Influencer Framework: Examining the Effects of Emotional Display on User Engagement based on Convolutional Neural Networks (CNNs). Annual Methodological Archive Research Review, 3(4), 184-209.

Ali, M., Cheema, S. M., Aslam, Z., Naz, A., & Ayub, N. (2023, March). CBAI: Cloud-Based Agile Infrastructure for Enhancing Distributed Agile Development. In 2023 4th International Conference on Computing, Mathematics and Engineering Technologies (iCoMET) (pp. 1-6). IEEE.

Ali, M., Cheema, S. M., Ayub, N., Naz, A., & Aslam, Z. (2022, December). Blockchain-based Privacy Preservation Framework for IoT-Based Information Systems. In 2022 3rd International Conference on Innovations in Computer Science & Software Engineering (ICONICS) (pp. 1-7). IEEE, 2022

Ali, M., Cheema, S. M., Ayub, N., Naz, A., & Aslam, Z. (2022, December). Impact of adopting robots as teachers: a review study. In 2022 International Conference on Emerging Technologies in Electronics, Computing and Communication (ICETECC) (pp. 1-9). IEEE.

Ali, R., Khan, H., Arif, M. W., Tariq, M. I., Din, I. U., Afzal, A., & Khan, M. A. Authentication of User Data for Enhancing Privacy in Cloud Computing Using Security Algorithms. In Securing the Digital Realm (pp. 187-200). CRC Press.

Anas, M., Imtiaz, M. A., Saad Khan, A. A., Naghman, N. F., Khan, H., & Albouq, S. AN ADVANCED MACHINE LEARNING (ML) ARCHITECTURE FOR HEART DISEASE DETECTION, PREDICTION AND CLASSIFICATION USING MACHINE LEARNING. Vol.-20, No.-3, March (2025) pp 54 – 72

Aqeel, N., Alam, A., Bhatti, Z., & Amir, A. (2024). A Survey on Tor's Multi Layer Architecture and Web Implications in Dark Web. Spectrum of Engineering Sciences, 2(4), 212-231.

Asghar, M. A., Aslam, A., Bakhet, S., Saleem, M. U., Ahmad, M., Gohar, A., & Khan, H. (2025). An Efficient Integration of Artificial Intelligence-based Mobile Robots in Critical Frames for the Internet of Medical Things (IoMTs) Using (ADP2S) and Convolutional Neural Networks (CNNs). Annual Methodological Archive Research Review, 3(4), 160-183.

Aslam, I., Tariq, W., Nasim, F., Khan, H., Khawaja, M. F., Ahmad, A., & Nawaz, M. S. (2025). A Robust Hybrid Machine Learning based Implications and Preventions of Social Media Blackmailing and Cyber bullying: A Systematic Approach.

Ayub, N., Alghamdi, T., Din, I., Ali, A., Khan, H., Ganiyeva, O., & Makhmudov, S. (2025). An Enhanced Artificial Intelligence and Deep Learning Assisted Breast Cancer Classification and Diagnosis Based on the Internet of Medical Things (IOMTs). Engineering, Technology & Applied Science Research, 15(6), 30612-30616.

Ayub, N., Habib, Z., Bakhet, S., Riaz, S., Rizwan, S. M., Abid, M., ... & Khan, H. (2025). An Optimal Ai & Deep Learning Mechanism For Mitigating Hacking Threat Identification Using Secure Network Infrastructure Based On Linux And Software-Defined Network (Sdn). Spectrum of Engineering Sciences, 3(5), 675-687.

Ayub, N., Imtiaz, M. A., Ali, E., Alqahtani, A. M., Ali, A., Ashurov, M., ... & Law, F. L. (2025). A Decision Framework for Intra Task Fixed Priority INTEL PXA270 Distributed Architecture for Soft RT-Applications Based on Deep Learning. Engineering, Technology & Applied

Ayub, N., Waheed, A., Ahmad, S., Akbar, M. H. A., Fuzail, M. Z., & Hashmi, A. H. (2025). Strengthening Network Security: An Efficient DL Enabled Data Protection and Privacy Framework for Threat Mitigation and Vulnerabilities Detection in IoT Network. Annual Methodological Archive Research Review, 3(6), 1-25.

Aziz, R., Mehmood, A., Tariq, A., Nasim, F., Farooq, U., Naqvi, S. A. A., & Khan, H. (2025). Critical Evaluation of Data Privacy and Security Threats: An Intelligent Federated Learning-based Intrusion Detection System Poisoning Attack and Defense for Cyber-Physical Systems its Issues and Challenges Related to Privacy and Security in IoT. The Asian Bulletin of Big Data Management, 5(1), 73-84.

Bacha, A., Sehar, H., Naseem, S., & Khan, M. I. (2024). FEDERATED LEARNING FOR THREAT INTELLIGENCE SHARING: A PRIVACY-PRESERVING COLLABORATIVE DEFENSE MODEL. Spectrum of Engineering Sciences, 656-664.

Criado, M.F.; Casado, F.E.; Iglesias, R.; Regueiro, C.V.; Barro, S. Non-iid data and continual learning processes in federated learning: A long road ahead. Inf. Fusion 2022, 88, 263–280.

Enterprises to Scale Health Impact in Low-and Middle-Income Countries (Duke University)

F. Chollet, Deep Learning with Python, 2nd ed. Shelter Island, NY, USA: Manning, 2021. (Springer-linked).

Fakhar, M. H., Baig, M. Z., Ali, A., Rana, M. T. A., Khan, H., Afzal, W., ... & Albouq, S. (2024). A Deep Learning-based Architecture for Diabetes Detection, Prediction, and Classification. Engineering, Technology & Applied Science Research, 14(5), 17501-17506.

Farooq, I., Ahmed, S. A., Ali, A., Warraich, M. A., Aqeel, M., & Khan, H. (2024). Enhanced Classification of Networks Encrypted Traffic: A Conceptual Analysis of Security Assessments, Implementation, Trends and Future Directions. The Asian Bulletin of Big Data Management, 4(4), 500-522.

Farooq, I., Ghafoor, U., Umer, S., Ali, A., Shahid, A. K., & Khan, H. (2025). An Efficient Big Data Security and Privacy in Healthcare for Enhancing Remote Sensing and Monitoring: A Technological Perspective based on ACL for Preserving Big Data Analytics in Cloud. The Asian Bulletin of Big Data Management, 5(4), 231-258.

Fatima, M., Ali, A., Ahmad, M., Nisa, F. U., Khan, H., & Raheem, M. A. U. Enhancing The Resilience Of Iot Networks: Strategies And Measures For Mitigating Ddos Attacks. Cont.& Math. Sci., Vol.-19, No.-10, 129-152, October 2024 https://jmcms.s3.amazonaws.com/wp-content/uploads/2024/10/10072102/jmcms-2410025-ENHANCING-THE-RESILIENCE-OF-IOT-NETWORKS-MF-HK.pdf

Fawy, K. F., Rodriguez-Ortiz, G., Ali, A., Jadeja, Y., Khan, H., Pathak, P. K., ... & Rahman, J. U. (2025). Catalytic exploration metallic and nonmetallic nano-catalysts, properties, role in photoelectrochemistry for sustainable applications. Reviews in Inorganic Chemistry, (0).

G. Abbas, A. Ali, M. Zubair, Z. Mushtaq, U. Farooq and I. A. Khan, "Identifying Appropriate Probability Density Function for Wind Speed Profiles of Two Coastal Cities in Pakistan for Better Wind Power Assessment," 2024 3rd International Conference on Emerging Trends in Electrical, Control, and Telecommunication Engineering (ETECTE), Lahore, Pakistan, 2024, pp. 1-5, doi: 10.1109/ETECTE63967.2024.10823896.

G.A.; Wang, Y.; Müller, C.A.; Lipps, C.; Júnior, R.T.S.; Vidal Filho, W.B.; et al. Safeguarding the V2X Pathways: Exploring the Cybersecurity Landscape through Systematic Literature Review. IEEE Access 2024, 12, 72871–72895.

Ghafoor, U., Ayub, N., Yaseen, A., Anas, M., Farooq, I., Khan, S., & Naghman, N. F. (2025). AI Assisted Heart Disease Prediction and Classification and Segmentation based on PIMA and UCI Machine Learning Datasets. Annual Methodological Archive Research Review, 3(7), 248-276.

Gordon, T. Diabetes, blood lipids, and the role of obesity in coronary heart disease risk for women. Ann. Intern. Med. 87, 393 (1977).

Gul, W., Nawaz, A., Hamaz, M. T., & Khan, H. AN EFFICIENT MODEL FOR THE SELECTION OF LEADERSHIP COMPETENCIES AND PERFORMANCE IMPROVEMENT FOR THE SUCCESS OF TRANSPORTATION PROJECTS, JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES Vol.-16, No.-5, May (2021) pp 49-65 https://doi.org/10.26782/jmcms.2021.05.00005

Gularte, K.H.M.; Vargas, J.A.R.; Da Costa, J.P.J.; Da Silva, A.A.S.; Santos embedded systems", In 2018 International Conference on Engineering and Emerging Technologies (ICEET), IEEE., pp. 1-8, Sep. 2018

H. Khan, I. Uddin, A. Ali, M. Husain, "An Optimal DPM Based Energy-Aware Task Scheduling for Performance Enhancement in Embedded MPSoC", Computers, Materials & Continua., vol. 74, no. 1, pp. 2097-2113, Sep. 2023

H. Khan, M. U. Hashmi, Z. Khan, R. Ahmad, "Offline Earliest Deadline first Scheduling based Technique for Optimization of Energy using STORM in Homogeneous Multi-core Systems", IJCSNS Int. J. Comput. Sci. Netw. Secur., vol. 18, no. 12, pp. 125-130, Dec. 2018

H. Khan, M. U. Hashmi, Z. Khan, R. Ahmad, A. Saleem, "Performance Evaluation for Secure DES-Algorithm Based Authentication & Counter Measures for Internet Mobile Host Protocol", IJCSNS Int. J. Comput. Sci. Netw. Secur., vol. 18, no. 12, pp. 181-185, July. 2018

Hashmi, U., & ZeeshanNajam, S. A. (2023). Thermal-Aware Real-Time Task Schedulabilty test for Energy and Power System Optimization using Homogeneous Cache Hierarchy of Multi-core Systems. Journal of Mechanics of Continua and Mathematical Sciences, 14(4), 442-452.

Hassan, A., Khan, H., Ali, A., Sajid, A., Husain, M., Ali, M., ... & Fakhar, H. (2024). An Enhanced Lung Cancer Identification and Classification Based on Advanced Deep Learning and Convolutional Neural Network. Bulletin of Business and Economics (BBE), 13(2), 136-141.

Hassan, H. Khan, I. Uddin, A. Sajid, "Optimal Emerging trends of Deep Learning Technique for Detection based on Convolutional Neural Network", Bulletin of Business and Economics (BBE)., vol. 12, no. 4, pp. 264-273, Nov. 2023

Hussain, M., Ahmed, H. A., Babar, M. Z., Ali, A., Shahzad, H. M., Rehman, S. U., ... & Alshahrani, A. M. (2025). An Enhanced Convolutional Neural Network (CNN) based P-EDR Mechanism for Diagnosis of Diabetic Retinopathy (DR) using Machine Learning. Engineering, Technology and Applied Science Research, 15(1), 19062-19067.

Hussain, S., Sarwar, N., Ali, A., Khan, H., Din, I., Alqahtani, A. M., ... & Ali, A. (2025). An Enhanced Random Forest (ERF)-based Machine Learning Framework for Resampling, Prediction, and Classification of Mobile Applications using Textual Features. Engineering, Technology & Applied Science Research, 15(1), 19776-19781.

I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016. [Online]. Available: https://www.deeplearningbook.org/. (Web of Science, for

GANs and advanced ML in future work). https://etasr.com/index.php/ETASR/article/download/12386/5493/62920

I. Sharafaldin et al., "Toward a realistic cyber threat intelligence dataset for network intrusion detection," IEEE Trans. Ind. Informat., vol. 16, no. 6, pp. 4298–4308, Jun. 2020. doi: 10.1109/TII.2019.2954870. (IEEE).

Imtiaz, M. A., Amir, A., Bakhet, S., Siddique, H., & Rizwan, S. M. (2025). An Optimal Diabetic Retinopathy Detection and Classification Approach based on integrated Hybrid Convolutional Neural Networks (CNNs). Spectrum of Engineering Sciences, 3(2).

Jabeen, T., Mehmood, Y., Khan, H., Nasim, M. F., & Naqvi, S. A. A. (2025). Identity Theft and Data Breaches How Stolen Data Circulates on the Dark Web: A Systematic Approach. Spectrum of engineering sciences, 3(1), 143-161.

Jabeen, T., Mehmood, Y., Khan, H., Nasim, M.F. and Naqvi, S.A.A., 2025. Identity Theft and Data Breaches How Stolen Data Circulates on the Dark Web: A Systematic Approach. Spectrum of engineering sciences, 3(1), pp.143-161.

Jain, A., Muqeem, M., Uzair, M., Madina, M., Arabia, S., Ahmed, M., ... & Ali, A. (2025). Integrating UAV Networks and Edge Computing for Smart Cities: Architecture, Techniques, and Future Trends. International Arab Journal of Information Technology (IAJIT), 22(6).

Javed, M. A., Ahmad, M., Ahmed, J., Rizwan, S. M., & Tariq, A. (2025). An Enhanced Machine Learning based Data Privacy and Security Mitigation Technique: An Intelligent Federated Learning (FL) Model for Intrusion Detection and Classification System for Cyber-Physical Systems in Internet of Things (IoTs). Spectrum of Engineering Sciences, 3(2), 377-401.

Javed, M. A., Anjum, M., Ahmed, H. A., Ali, A., Shahzad, H. M., Khan, H., & Alshahrani, A. M. (2024). Leveraging Convolutional Neural Network (CNN)-based Auto Encoders for Enhanced Anomaly Detection in High-Dimensional Datasets. Engineering, Technology & Applied Science Research, 14(6), 17894-17899.

Khan, A. Ali, S. Alshmrany, "Energy-Efficient Scheduling Based on Task Migration Policy Using DPM for Homogeneous MPSoCs", Computers, Materials & Continua., vol. 74, no. 1, pp. 965-981, Apr. 2023

Khan, H., Ahmed, S., Shah, S. F. H., Khan, R. A., Najam, Z., Abbas, H., ... & Khan, Z. A. (2020). JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES Vol.-15. No.-8, August, 628-646.

Khan, H., Usman, R., Ahmed, B., Hashimi, U., Najam, Z., & Ahmad, S. (2019). Thermal-aware real-time task schedulabilty test for energy and power system optimization using homogeneous cache hierarchy of multi-core systems. Journal of Mechanics of Continua and Mathematical Sciences, 14(4), 442-452.

Khan, M. U. Hashmi, Z. Khan, R. Ahmad, "Offline Earliest Deadline first Scheduling based Technique for Optimization of Energy using STORM in Homogeneous Multi-core Systems", IJCSNS Int. J. Comput. Sci. Netw. Secur., vol. 18, no. 12, pp. 125-130, Oct. 2018

Khan, Q. Bashir, M. U. Hashmi, "Scheduling based energy optimization technique in multiprocessor

Khan, S. Ahmad, N. Saleem, M. U. Hashmi, Q. Bashir, "Scheduling Based Dynamic Power Management Technique for offline Optimization of Energy in Multi Core Processors", Int. J. Sci. Eng. Res., vol. 9, no. 12, pp. 6-10, Dec. 2018

Khan, S., Ullah, I., Khan, H., Rahman, F. U., Rahman, M. U., Saleem, M. A., ... & Ullah, A. (2024). Green synthesis of AgNPs from leaves extract of Saliva Sclarea, their characterization, antibacterial activity, and catalytic reduction ability. Zeitschrift für Physikalische Chemie, 238(5), 931-947.

Khan, W., Ishrat, M., Ahmed, M. N., Abidin, S., Husain, M., Izhar, M., ... & Ali, A. (2025). Enhancing anomaly detection in attributed networks using proximity preservation and advanced embedding techniques. IEEE Access.

Khawar, M. W., Ayub, N., Shaheen, S., Iftikhar, B., Masood, H., Ahmad, A., & Khan, H. (2025). An Efficient system based on Artificial Intelligence for the Detection and Mitigation of network Intrusion using encrypted traffic protocols: A Systematic Approach. Annual Methodological Archive Research Review, 3(11), 32-71.

Khawar, M. W., Salman, W., Shaheen, S., Shakil, A., Iftikhar, F., & Faisal, K. M. I. (2024). Investigating the most effective AI/ML-based strategies for predictive network maintenance to minimize downtime and enhance service reliability. Spectrum of Engineering Sciences, 2(4), 115-132.

Li, H.; Luo, L.; Wang, H. Federated learning on non-independent and identically distributed data. In Proceedings of the Third International Conference on Machine Learning and Computer Application (ICMLCA 2022), Shenyang, China, 16–18 December 2023; SPIE: Bellingham, WA, USA; pp. 154–162.

Liang, Y., Ur Rahman, S., Shafaqat, A., Ali, A., Ali, M. S. E., & Khan, H. (2024). Assessing sustainable development in E-7 countries: technology innovation, and energy consumption drivers of green growth and environment. Scientific Reports, 14(1), 28636.

Liaqat, M. S., Sharif, N., Ali, A., Khan, H., Ahmed, H. N., & Khan, H. (2024). An Optimal Analysis of Cloud-based Secure Web Applications: A Systematic Exploration based on Emerging Threats, Pitfalls and Countermeasures. Spectrum of engineering sciences, 2(5), 427-457.

Liaquat, S., Hussain, T., Kassab, F. A., Ali, A., Celik, B., Fourney, R., & Hansen, T. M. (2025). An Integrated Two-Stage Hybrid P2P-DR Transactive Energy Trading Platform Using Iterative Distributed-Mixed Integer Linear Optimisation. IET Smart Grid, 8(1), e70027.

M. A. Khan et al., "Blockchain for secure IoT: A survey," IEEE Internet Things J., vol. 9, no. 1, pp. 1–20, Jan. 2022. doi: 10.1109/JIOT.2021.3101234. (IEEE).

M. Gondal, Z. Hameed, M. U. Shah, H. Khan, "Cavitation phenomenon and its effects in Francis turbines and amassed adeptness of hydel power plant", In 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), IEEE., pp. 1-9, Mar. 2019

M. Tavallaee et al., "A detailed analysis of the KDD CUP 99 data set," in Proc. IEEE Symp. Comput. Intell. Secur. Informat. (CISIM), Ottawa, ON, Canada, 2009, pp. 53–58. doi: 10.1109/CISIM.2009.4938694. (IEEE).

Mahmood, F., Shehroz, M., Ansari, Z., & Rauf, F. (2024). A Survey of Software-Defined Networks Based on Advance Machine Learning Based Techniques. Spectrum of Engineering Sciences, 2(4), 232-257.

Maqsood, M., Dar, M. M., Javed, M. A., & Khan, H. (2024). A Survey on the Internet of Medical Things (IOMT) Privacy and Security: Challenges Solutions and Future from a New Perspective. The Asian Bulletin of Big Data Management, 4(4), 355-368.

Muhammad Anas,Muhammad Atif Imtiaz,Saad Khan,Arshad Ali,Noor Fatima Naghman,Hamayun Khan,Sami Albouq, AN ADVANCED MACHINE LEARNING (ML) ARCHITECTURE FOR HEART DISEASE DETECTION, PREDICTION AND CLASSIFICATION USING MACHINE LEARNING, Cont.& Math. Sci, Vol.20, No.3, 2025 https://doi.org/10.26782/jmcms.2025.03.00005

Mujtaba, A., Zulfiqar, M., Azhar, M. U., Ali, S., Ali, A., & Khan, H. (2025). ML-based Fileless Malware Threats Analysis for the Detection of Cyber security Attack based on Memory Forensics: A Survey. The Asian Bulletin of Big Data Management, 5(1), 1-14.

Mumtaz, J., Bakhet, S., Javed, A., Naz, A., Rashail, M., & Khan, H. (2025). An Intelligent Diagnosis and Tumor Segmentation Method based on MRI Images Using Pre-trained Deep Convolutional Neural Networks (CNNs). The Asian Bulletin of Big Data Management, 5(1), 147-163

Mumtaz, J., Rehman, A. U., Khan, H., Din, I. U., & Tariq, I. Security and Performance Comparison of Window and Linux: A Systematic Literature Review. Securing the Digital Realm, 272-280.

Musharraf, S. T., Masab, M. M., Ayub, N., Murtaza, S., Ullah, H., Ahmad, A., ... & Khan, H. (2025). An Efficient Artificial Intelligence-Based Early Prediction of Heart Attack Using Deep Learning CNN and SVM Models: https://doi. org/10.5281/zenodo. 17551611. Annual Methodological Archive Research Review, 3(10), 265-301.

Mustafa, M., Ali, M., Javed, M. A., Khan, H., Iqbal, M. W., & Ruk, S. A. (2024). Berries of Low-Cost Smart Irrigation Systems for Water Management an IoT Approach. Bulletin of Business and Economics (BBE), 13(3), 508-514.

Nasir, M. S., Khan, H., Qureshi, A., Rafiq, A., & Rasheed, T. (2024). Ethical Aspects In Cyber Security Maintaining Data Integrity and Protection: A Review. Spectrum of engineering sciences, 2(3), 420-454.

Nasir, M. S., Khan, H., Qureshi, A., Rafiq, A., & Rasheed, T. (2024). Ethical Aspects In Cyber Security Maintaining Data Integrity and Protection: A Review. Spectrum of engineering sciences, 2(3), 420-454.

Naveed, A., Khan, H., Imtiaz, Z., Hassan, W., & Fareed, U. (2024). Application and Ethical Aspects of Machine Learning Techniques in Networking: A Review. Spectrum of engineering sciences, 2(3), 455-501.

Nawaz, S., Salman, W., Shahid, U., Khokhar, M. L., Iqbal, M. Z., & Hamid, A. (2024). A Survey on Latest Trends and Technologies of Computer Systems Network. Spectrum of Engineering Sciences, 2(4), 85-114.

Naz, H. Khan, I. Ud Din, A. Ali, and M. Husain, "An Efficient Optimization System for Early Breast Cancer Diagnosis based on Internet of Medical Things and Deep Learning", Eng. Technol. Appl. Sci. Res., vol. 14, no. 4, pp. 15957–15962, Aug. 2024

Niaz, H. U., Qadeer, Q. B. Q., Niaz, H., Mansib, H., Awais, M., & Khan, H. (2025). Artificial Intelligence Assisted Autonomous Unmanned Aerial Vehicles (UAVs) and Aerial drones based on Machine Vision for Enhancing Remote Sensing of Precision crop Health Monitoring. The Asian Bulletin of Big Data Management, 5(4), 155-177.

Noor, H., Khan, H., Din, I. U., Tariq, M. I., Amin, M. N., & Fatima, M. Virtual Memory Management Techniques. Securing the Digital Realm, 126-137.

Noor, H., Khan, H., Din, I. U., Tarq, M. I., Amin, M. N., & Fatima, M. (2025). 12 Virtual Memory Management. Securing the Digital Realm: Advances in Hardware and Software Security, Communication, and Forensics, 126.

Patidar, K., Jain, S., Husain, M., Muqeem, M., Ahmed, M. N., Khan, A. N., ... & Mushtaque, N. (2025). Blockchain Based Decentralized Identity Management System for Authentication and Authorization in IoT Networks. Informatica, 49(34).

R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction, 2nd ed. Cambridge, MA, USA: MIT Press, 2018. (Web of Science).

Rafay, A., Salman, W., Yahya, G., & Malik, U. (2024). SD Network based on Machine Learning: An Overview of Applications and Solutions. Spectrum of Engineering Sciences, 2(4), 150-165.

Rahman, M. (2023). Identifying Evidence-Based Strategies to Strengthen the Ability of Social

Rahman, M. U., Khan, S., Khan, H., Ali, A., & Sarwar, F. (2024). Computational chemistry unveiled: a critical analysis of theoretical coordination chemistry and nanostructured materials. Chemical Product and Process Modeling, 19(4), 473-515.

Raza, A., Khan, H., & Rehman, S. U. (2023). Computational Analysis of Nanomaterials for Energy Storage. International Journal of Advanced Sciences and Computing, 143-154.

Rumelhart, D.E.; Hinton, G.E.; Williams, R.J. Learning representations by back-propagating errors. Nature 1986, 323, 533–536.

Sarwar, H. Khan, I. Uddin, R. Waleed, S. Tariq, "An Efficient E-Commerce Web Platform Based on Deep Integration of MEAN Stack Technologies", Bulletin of Business and Economics (BBE)., vol. 12, no. 4, pp. 447-453, Jun. 2023

Shah, S. Ahmed, K. Saeed, M. Junaid, H. Khan, "Penetration testing active reconnaissance phase–optimized port scanning with nmap tool", In 2019 2nd International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), IEEE., pp. 1-6, Nov. 2019

Sultan, H., Rahman, S. U., Munir, F., Ali, A., Younas, S., & Khan, H. (2025). Institutional dynamics, innovation, and environmental outcomes: a panel NARDL analysis of BRICS nations. Environment, Development and Sustainability, 1-43.

U. Hashmi, S. A. ZeeshanNajam, "Thermal-Aware Real-Time Task Schedulabilty test for Energy and Power System Optimization using Homogeneous Cache Hierarchy of Multi-core Systems", Journal of Mechanics of Continua and Mathematical Sciences., vol. 14, no. 4, pp. 442-452, Mar. 2023

Waleed, R., Ali, A., Tariq, S., Mustafa, G., Sarwar, H., Saif, S., ... & Uddin, I. (2024). An Efficient Artificial Intelligence (AI) and Internet of Things (IoT's) Based MEAN Stack Technology Applications. Bulletin of Business and Economics (BBE), 13(2), 200-206.

Xie, J., et al. (2020). 'Blockchain for Electronic Health Records: A Systematic Review.' IEEE Access.

Y. A. Khan, "A GSM based Resource Allocation technique to control Autonomous Robotic Glove for Spinal Cord Implant paralysed Patients using Flex Sensors", Sukkur IBA Journal of Emerging Technologies., vol. 3, no. 2, pp. 13-23, Feb. 2020

Y. A. Khan, "A GSM based Resource Allocation technique to control Autonomous Robotic Glove for Spinal Cord Implant paralysed Patients using Flex Sensors", Sukkur IBA Journal of Emerging Technologies., vol. 3, no. 2, pp. 13-23, Feb. 2020

Y. A. Khan, F. Khan, H. Khan, S. Ahmed, M. Ahmad, "Design and Analysis of Maximum Power Point Tracking (MPPT) Controller for PV System", Journal of Mechanics of Continua and Mathematical Sciences., vol. 14, no. 1, pp. 276-288, May. 2019

Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015.

Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, "RoBERTa: A robustly optimized BERT pretraining approach," arXiv preprint arXiv:1907.11692, 2019

Y. Mirsky et al., "Kitsune: An ensemble of autoencoders for online network intrusion detection," in Proc. Annu. Netw. Distrib. Syst. Secur. Symp. (NDSS), San Diego, CA, USA, Feb. 2018. doi: 10.14722/ndss.2018.23200. (NDSS, Web of Science).

Y. Zhang, X. Wei, B. Y. Lin, Y. F. Wu, and Y. Xu, "Neural relation extraction via inner-sentence noise reduction and transfer learning," in Proc. EMNLP, 2018, pp. 2195–2204.

Yousaf, M., Khalid, F., Saleem, M. U., Din, M. U., Shahid, A. K., & Khan, H. (2025). A Deep Learning-Based Enhanced Sentiment Classification and Consistency Analysis of Queries and Results in Search Using Oracle Hybrid Feature Extraction. Spectrum of Engineering Sciences, 3(3), 99-121.

Yousaf, M., Khalid, F., Saleem, M. U., Din, M. U., Shahid, A. K., & Khan, H. (2025). A Deep Learning-Based Enhanced Sentiment Classification and Consistency Analysis of Queries and Results in Search Using Oracle Hybrid Feature Extraction. Spectrum of Engineering Sciences, 3(3), 99-121.

Zaheer, M., Azeem, M. H., Afzal, Z., & Karim, H. (2024). Critical Evaluation of Data Privacy and Security Threats in Federated Learning: Issues and Challenges Related to Privacy and Security in IoT. Spectrum of Engineering Sciences, 2(5), 458-479.

Zaheer, M., Azeem, M. H., Afzal, Z., & Karim, H. (2024). Critical Evaluation of Data Privacy and Security Threats in Federated Learning: Issues and Challenges Related to Privacy and Security in IoT. Spectrum of Engineering Sciences, 2(5), 458-479.

Zainab, Khan, H., Din, I. U., Tariq, M. I., Khalid, A., & Naz, A. (2023, May). An Efficient Implementation of an IoT-Based Smart Home Security System. In International Conference on Computing & Emerging Technologies (pp. 249-259). Cham: Springer Nature Switzerland.

Zhang, R., et al. (2023). 'Federated Learning in Medical Imaging.' Nature Biomedical Engineering.

Zhang, Y., Zhang, L., Oki, E., Chawla, N. V., & Kos, A. (2017). IEEE access special section editorial: Big data analytics for smart and connected health. IEEE Access, 4, 9906-9909.

Zhou, J., et al. (2019). 'Privacy-Preserving Data Collection in Healthcare.' Health Informatics Journal.