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Optimizing NLP-Text Classification in Knowledge Management Systems: A Literature Review

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ABSTRACT: Knowledge Management Systems (KMS) are required to organize and assign meaning to huge amounts of organizational knowledge that are largely in the form of unstructured text. Natural Language Processing (NLP), and more immediately methods of text categorization, has been one of the principal enabler technologies to enable KMS to be simpler by helping to automatically categorize documents, enhance searching for information, and assist in decision-making. This paper offers an outline of the evolution of NLP-based text classification methods from initial machine learning methods such as Naïve Bayes and Support Vector Machines to current sophisticated deep learning algorithms such as Convolutional Neural Networks, Recurrent Neural Networks, and Transformers. We offer real-world industry use cases, issues of scalability, explainability, and ethics and encapsulate research areas of existing gaps. The findings underscore the enormous potential of NLP text classification to assist the effectiveness and efficiency of knowledge management (KM) activities.

KEYWORDS: Artificial Intelligence, Knowledge Management Systems, Natural Language Processing, Integration

I. INTRODUCTION

In a data-driven economy, effective knowledge management (KM) is essential for organizations to thrive. Knowledge Management Systems (KMS) play an important role in collecting, organizing, and disseminating both the explicit and implicit knowledge within businesses. However, because organizations are increasingly relying upon digital communications and documentation, the complex and voluminous amount of unstructured text data continues to burden knowledge management (KM). The limitations of traditional KMS specific to addressing voluminous, dynamic, and heterogeneous text data have been recognized by researchers ((Dalkir, 2011); (Maier, 2007)). To address knowledge management (KM) challenges, Natural Language Processing (NLP), particularly text classification, has offered powerful solutions that help to optimize knowledge management (KM)workflows.

Text Classification is the automatic assignment of labels or categories to textual documents, assisting in organizing and finding information. Text classification is used extensively in spam detection, sentiment analysis, document classification, etc. As stated by (Aggarwal & Zhai, 2012), text classification facilitates several information retrieval tasks by making content more structured and providing smarter search and recommendation engines. These techniques applied to KMS very well improves the manner knowledge is captured, indexed, and retrieved.

Recent developments in NLP, particularly in those based on deep learning and the transformer architecture, have provided possibilities in deepening the applicability of KMS. The Transformer model was introduced by Vaswani (Vaswani et al, 2017)and underpins the state-of-the-art text classifiers, like BERT (Devlin et al, 2019). Knowledge graphs, which seek to represent the meanings of entities and their related concepts, were previously limited to tagged or categorized representations of knowledge resources in KMS. From an NLP perspective, many of the new advances have been contextualized due to understanding both context and semantics, which allows for greater classification of knowledge resources. Zhang (Zhang et al, 2020) showed that contextualized embedding provided significant gains over bag-of-words models for tasks related to the classification of enterprise documents.

Within knowledge management (KM), the application of text classification can address some key challenges. For instance, (Wu & Wang, 2006) KMS, because of the amount of "knowledge overload" that users experience, are one of the most persistent problems in knowledge management systems (KMS) that users face. Relevant knowledge can be buried under irrelevant information and outdated knowledge.

Automated classification can provide relief to this issue, while also effectively tagging and sorting documents, some of the relational and contextual relevance can be excavated when a user retrieves documents. Additionally, (Lin & Hsueh, 2010) intelligent classification not only allows for a user to access information from KMS but also to discover knowledge. If the document is properly tagged, users are not limited by their queries and much greater outcomes for the worth of KMS are achieved.

In addition, NLP classification is useful because it provides immediate taxonomy creation and modification of taxonomies. In a dynamic context, (Lee & Lee, 2021) fluidity is required due to the rapid changes in the knowledge domain of many different industries. Current KMS systems do not have the agile capabilities to incorporate these changes in real time, however, a machine learning classifier could be retrained periodically or continuously in order to leverage an improved variety of terminology and topic, or organizational structure.

However, there are challenges to integrating NLP classification into KMS. First,(Chen et al, 2015) the effectiveness of text classification in KMS relies upon the quality and representativeness of training data. Abbreviations as well as domain language and differences in document format can reduce the classification effectiveness. In addition, organizations must work within meta-structure with regards to issues such as model interpretability and data privacy. Some form of transparency is needed for NLP models in an enterprise context, to ensure that users will remain confident that whatever classification result produced by the model confirms their understanding of their findings (Ribeiro et al, 2016).

The purpose of this paper is to establish the theoretical and practical grounding for the application of NLP text classification to enhance KMS. We will explore the literature and the methods themselves from prominent techniques in classical machine learning, for example, Naïve Bayes and support vector machine to modern deep learning like CNNs, RNNs, and Transformers. Subsequently, we will investigate how organizations have employed these methods for the purposes of better knowledge discovery, reduced information silos and improved decision support. Lastly, we will discuss recommendations for the future and develop a framework for scaling NLP classification into enterprise KMS both responsibly and ethically.

By drawing, combining and synthesizing the top researchers and practitioners, this effort will help to further our understanding of how NLP text classification can evolve traditional knowledge management (KM) into more intelligent, responsive, and client-centric systems.

II. LITERATURE REVIEW

A. Introduction to Knowledge Management Systems (KMS)

Knowledge Management Systems (KMS) are organizational tools designed to create, capture, store, and share knowledge. KMS are a technological and organizational base for knowledge processes and decision making, they mean that KMS are IT-based systems designed to support and enhance knowledge creation, storage/retrieval, transfer and application in organizations (Alavi & Leidner, 2001) .KMS is more than just technology, but fit within a broader socio-technical system where culture, structure and people hold important roles in the socio organization, which means that successful project changes in KMS are no less dependent on human and organizational aspects than they are on technology (Davenport & Prusak, 1998) . Figure 1 presents a synthesized illustration of the Knowledge Management System processes described by Alavi and Leidner (2001).

Figure 1. Knowledge Management System Processes Source: Author's synthesis based on Alavi and Leidner (2001).

Figure 1 illustrates the key Knowledge Management System (KMS) processes described by Alavi and Leidner (2001). It shows that effective knowledge management is achieved through four interrelated processes: knowledge creation, knowledge storage and retrieval, knowledge transfer, and knowledge application. Together, these processes facilitate the generation, organization, sharing, and effective use of organizational knowledge to support informed decision-making and improve organizational performance. The figure also provides a useful conceptual basis for understanding how emerging technologies such as Natural Language Processing (NLP) can enhance these processes by improving the classification, retrieval, and accessibility of organizational knowledge.

Knowledge in organizations can take two forms, tacit and explicit, and that "conversion" across categories is important. KMS facilitate conversion by preserving the tacit (e.g. collaboration and expert remarks) and storing the explicit (e.g. databases/docs), which supports Nonaka's SECI

knowledge development process: Socialization, Externalization, Combination and Internalization (Nonaka & Takeuchi, 1995).More recently a more comprehensive definition of KMS that blends information systems, knowledge management (KM), and organizational theory was provided by Maier and Hädrich. They argue that more recent KMS must support the user-oriented knowledge work by providing contextual, timely, and relevant information with less information overload (Maier & Hädrich, 2009) . Nonaka's SECI knowledge development process can be summarized in the diagram below.

Heisig, in their review of KMS evolution, analyzed more than 160 models of knowledge management (KM), and overview of a generalized model, has identified common relations involving key processes of knowledge management (KM) like identifying, acquiring, developing, sharing and utilizing knowledge. He also recognized that technology was a critical enabler, particularly for large organizations that are geographically distributed (Heisig, 2009).

In their research, (Gold et al., 2001) presented evidence that implementing KMS successfully leads to enhanced organizational performance when organization capability with respect to identifying knowledge related infrastructure (technology, structure and culture) is present. Their work illustrates the strategic importance of KMS and its support role in leveraging organization capabilities for an organization to achieve their strategic goals.

According to (Mutua et al., 2024) Implementing effective knowledge management (KM) practices can significantly improve how healthcare organizations operate. By streamlining processes and promoting better communication among staff, organizations can reduce duplication of work and enhance overall workflow. This not only saves time in both administrative and clinical tasks but also ensures that resources are used more efficiently. As a result, healthcare facilities can lower their operating costs while maintaining or even improving the quality of services.

In conclusion, a variety of scholars and researchers agree that KMS are complex systems that consist of technology, people, and processes and are developed to trigger stronger flows of organizational knowledge. They also agree that KMS effectiveness is contingent on both its ability to store and surface knowledge but also in the extent to which it fosters to knowledge sharing, learning, and innovation. Complexity encompasses many perspectives and creates a foundation for evaluating whether and how technologies like Natural Language Processing (NLP) might further enhance KMS functionality, particularly with regard to the processing and classification of increasingly large volumes of unstructured text.

B. The Role of NLP- text classification in Enhancing KMS

Through text classification methods, Natural Language Processing (NLP) has been a powerful enabler of Knowledge Management Systems (KMS) and has been an area of focused research to understand its potential impact on KMS or KM-related capabilities. Study of the integration of NLP with KMS highlights its ability to not only improve knowledge discovery and knowledge sharing but also de-normalize information silos and ultimately facilitate decision-making and strategic decision-making.

Knowledge retrieval is largely dependent on the ability of the KMS (content) to classify and index appropriately. Text classification is a branch of NLP that will automatically classify documents, emails, and other forms of organizational communication within appropriate categories, effectively creating contextual meaning and providing access to large quantities of organizational knowledge. This capability makes a passive repository of information into a proactive knowledge system (Dumais, 2004). Concisely, NLP (which includes sentiment analysis and semantic parsing) has improved the detail and precision of document classification. Where KMS are used, NLP may offer more useful knowledge recommendations and deliver user-focused content, thus offering a more useful knowledge acquisition mechanism across hierarchical and departmental differences (Cambria & White, 2014).

In addition to streamlining document classification, reducing the manually assigned information loss due to siloing is the oldest problem in KM. Through text classification, organizations may standardize describing knowledge and improve interoperability. This is crucial in large organizations where knowledge is divided among many departments (Feldman & Sanger, 2007).In addition, NLP-based classifications aid organization-based decision-making. If knowledge is structured and classified correctly, then decision-makers can glean actionable information faster. For example, the classification of incident reports and policy documents can reveal systemic problems and lead to policy changes (Firestone & McElroy).

In addition, new advances in deep learning-based NLP are also increasing KMS capabilities. Zhang showed that contextualized embeddings (e.g., BERT) performed better than keyword-based classifications for enterprise

document management systems. Such models could consider the subtlety of language and achieve greater accuracy in classifications in fields with complex language such as finance or law (Zhang et al, 2020) . Maier (Maier R. , 2007) also discusses the user experience aspect of NLP adoption in KMS. Intelligent text classification improves the user experience through recommending knowledge items based on users' tasks and other preferences. This increases user participation and cultivates a knowledge-sharing and collaborative culture. Adaptability is an important advantage of NLP classification. Borkar (Borkar & Deshmukh, 2018) found that many recent classification systems have become robust enough in classification practices to continue adapting to existing changes in language and terminology used within the organization or niche. The result is that KMS can stay up to date and relevant in practice despite expansion and change in content over time. Adopting NLP-based classification as part of larger operational business process, such as customer service and compliance monitoring or employee onboarding, enables firms to fully engage with those core KMS and define operational KMS. When KMS are connected through the use of classification API into an operational system (including customer self-service) the KMS becomes a type of intelligent support that helps enhance productivity by connecting staff with knowledge items without redundancy of information (Chiticariu et al, 2010).

Ultimately, the incorporation of NLP into KMS mirrors a more extensive interdisciplinary shift occurring in information systems research. Heisig compared (Heisig, 2009) beyond 160 KM models and concluded that good knowledge systems need to adopt knowledge from linguistics, artificial intelligence, organizational behavior and information retrieval in order to fully engage their potential. Text classification thus helps connect these fields, allowing for the overall management of tacit and explicit knowledge.

C. Classical machine learning techniques versus deep learning approaches for text classification

Many researchers have performed comparisons of traditional machine learning algorithms against deep learning methods for text classification and discussed their relative advantages and disadvantages across a range of scenarios. In their pioneering text Mining Text Data (Aggarwal & Zhai, 2012), the authors discussed traditional models such as Naive Bayes, Support Vector Machines (SVMs), and decision trees and pointed out that these models work well with technique types of model conditioning in the feature engineering tradition (e.g., TF-IDF, or framing of data using n-grams). This allowed the authors to acknowledge the limitation of classical algorithms and their tendency not to really model the language in the domain, as they struggle to model the semantic and contextual dimensions of the language.

Zhang (Zhang et al., 2015) provide one of the earliest large-scale empirical comparisons using traditional models as the placed product against deep convolutional neural networks (CNN), and trained to model input at the character level. In particular, the analyses demonstrate CNN constructs significantly perform better than traditional models, therefore suggesting that CNN methods are favorable to traditional methods primarily because, when trained on large data with word dependency contexts, CNN models are able to incorporate deep context with a hierarchical structure. Complementary to this work, Kim (Kim, 2014) used building convolutional type algorithms in relation to SVM and logistic regression for sentence-level classification and finds that CNN's showed marked performance improvements beyond SVMs and logistic regression because deep learning methods are able to incorporate local contextual dependencies and preserve some syntactic variation better.

FastText was introduced by Joulin (Joulin et al., 2016) as a shallow neural network model and acts as a bridge between classical methods and deep learning. FastText demonstrated that it matched or exceeded existing models but had the same level of computational efficiency that is so commonly associated with classical computational techniques. Moreover, FastText showed that the same advancements experienced with deep learning could have been attained by not developing models that require significant computational work, like deeper or more recurrent networks.

The quick move towards contextual language understanding was aided by transformer models, including BERT, which was shown (Devlin et al, 2019) to achieve significant improvements over classical and early deep learning methods and outperformed them in a wide range of benchmark NLP tasks. Specifically, BERT was able to understand bidirectional context as well as the context of each word by surrounding words, and this capability led to the establishment of a new benchmark for text classification, out-performing classical and earlier deep-learning approaches in the fields of sentiment analysis, question answering, and natural language inference.

D. Deep Learning for Text Classification

i. Convolutional Neural Networks (CNNs)

Kim (Kim, 2014) adapted CNNs for sentence classification and successfully demonstrated that CNNs have the capacity to capture local semantic structures. In KMS, CNNs can be used to examine short documents or snippets such as FAQs or descriptions of policies. Johnson and Zhang (Johnson & Zhang, 2016) extended their work and developed region-based CNNs that provided high-level representations for better contextual capturing of a document. Both of these extensions have been effective at segmenting and classifying

knowledge components contained within a larger document in enterprise repositories.

ii. Recurrent Neural Networks (RNNs) and long-short-term memory networks (LSTMs)

RNNs including LSTMs were developed to work with sequential data. Liu utilized LSTMs within KMS to classify meeting transcripts, and lengthy operating procedure documents. RNNs and LSTMs capture long-term dependencies which make them available for capturing document contexts. Hochreiter and Schimdhuber (Hochreiter & Schmidhuber, 1997) introduced LSTMs, which have memory cells that allow an RNN to preserve important information over longer sequences. Hochreiter and Schmidhuber argue the importance of their work relates to progression of an issue: instead of dealing with complete dilution of information within a KMS text analysis or capturing the entire document, LSTMs effective preserve important information over long-term**.**

iii. Transformers and BERT

The advent of transformers (Vaswani et al, 2017) has fundamentally changed natural language processing by allowing models to learn contextual relationships through entire documents. BERT (Devlin et al, 2019), a bidirectional encoder, raised the state-of-the-art and matched performance in text classification. Zhang (Zhang et al, 2020) have introduced BERT-based enterprise KMS that have automated document classification with much greater accuracy and flexibility than existing models. BERT was improved even further (Sun et al, 2019) through domain specific fine-tuning (SciBERT, BioBERT), achieving, for instance, vastly superior classification in KMS for certain subject areas, such as academia and biomedicine.

E. Practical applications in organizations

i. Healthcare

NLP classification has been applied in the healthcare sector to organize clinical notes, facilitate patient-level data access, and provide decision support. By using NLP classification, the clinician cognitive burden is reduced and easy access to relevant knowledge is improved. Wang (Wang et al., 2018) applied deep neural networks to automatic classify radiology reports. The machine-classified radiology reports assured better integration into the electronic health record (EHR) systems and improved diagnostic workflows.

ii. Finance

In finance, text classification has been implemented for regulatory compliance checks, download customer sentiment from customer feedback, and to tag documents (Zhang et al, 2020). NLP has improved indexing and discoverability of sensitive financial documents, as well as the finding, and processing, of sensitive financial documents. It was asserted that (Chiticariu et al, 2010) the proposed rule-based and ML-based hybrid methods typically outperform either single method in finance, especially with commonly used regulatory language and jargon in finance.

iii. Education and Research

Universities have used NLP enhanced KMS to manage academic resources, index research publications, and facilitate collaboration. The NLP process of text classification made content easier to discover and allow for less duplication of original content documents (Lee & Lee, 2021). The idea of using contextual embeddings from language models like ELMo and BERT to inform re-classification of academic literature into knowledge concepts based on indexing and retrieval practices was brought out (Peters et al , 2018) .The following is a diagram that summarizes some of the applications of KMS using NLP

III. CHALLENGES AND ETHICAL CONSIDERATIONS

A. Data quality and domain sensitivity

NLP models depend on the appropriate support of data quality and the usage of consistent language. It is important to recognize that domain differences in vocabulary can lead to inconsistent performance by models. Domain adaptation (Chen et al, 2015)can be critical in realizing the full power of NLP in specialized situations like KMS. Pan and Yang (Pan & Yang, 2010) provided general conclusions from their transfer learning research in support of repurposing annotated data from one domain to help with performance in a different domain, an approach we are now seeing in general to address multi-domain KMS.

B. Model interpretability

Interpretable models are needed both to support transparency of classification outcomes needed by decision-makers and to maintain expectations of accountability in enterprise situations (Ribeiro et al, 2016). Interpretable classification by models not only benefits users needing to trust decision—but also to be expected to be accountable. Frameworks for rigorously evaluating interpretability features of machine learning are offered (Doshi-Velez & Kim, 2017). The importance of models being interpretable seems obvious when users may be accountable in performance situations (e.g., accident investigation, medical diagnosis, etc.).

C. Ethical and privacy issues

As organizations integrate NLP-text classification into KMS, several ethical and privacy challenges arise. Researchers highlight concerns around data privacy, where sensitive internal documents may be exposed or used without consent (Shokri & Shmatikov, 2015). There is also the risk of algorithmic bias, which can reinforce stereotypes and lead to unfair decision-making (Mehrabi et al., 2021). The lack of transparency in complex models like transformers poses issues for accountability (Doshi-Velez & Kim, 2017), while questions of data ownership remain unresolved, particularly when employee-generated knowledge is commodified (Zuboff, 2019).

IV. RESEARCH GAPS

A. Domain-Specific Adaptation

Researchers argue that NLP models consistently underperform across distinct domains because of the vocabulary, terminology, and context differences (Chen et al, 2015); (Lee et al, 2020). The lack of sufficient annotated domain-specific data limits the effective fine-tuning general-purpose NLP models (Pan & Yang, 2010). Although fine tuning domain-specific information has advantages, transfer learning still requires large amounts of in-domain data with limited or sometimes no available data. Researchers recommend we increase the efficacy of domain adaptation methods, including few-shot and unsupervised learning, and domain specific language models to improve the accuracy and applicability of classification in different Knowledge Management Systems (KMS).

B. Handling Unstructured and Multimodal Data

Researchers have pointed out that the vast majority of NLP text classification models are directed toward structured-text or unstructured text, yet the organizational knowledge doesn't necessarily consist of just text documents; it might include unstructured information in addition to images, audio, videos, and complex document structures (Kumar et al., 2021); (Zhang et al, 2020).Prior methodologies can only analyse unstructured and structured data separately, meaning the system cannot fully assess organizational knowledge. There is a notable gap in generating an effective multimodal learning paradigm that can jointly process and classify heterogeneous knowledge sources which would increase retrieval accuracy and decision support in KMS.

C. Scalability and Real-Time Processing

Researchers have shown that despite advances in NLP-text classification, most recent techniques are computationally costly and are not ready for deployment for large-scale or real-time use in Knowledge Management Systems (KMS) in the enterprise (Parisi et al., 2019). In fact, many current models require unmanageable amounts of processing power and memory, thus hindering the ability to create real-time responsive systems that can incorporate continuous incoming knowledge streams. On the other hand, needing to perform real-time analytics with dynamic organizational data, particularly for latency-sensitive applications (e.g., live customer service, or crisis management), remains a challenge. In light of either scalable architectures (e.g., real-time NLP pipelines, edge computing, or continual learning model methods) or lightweight models that are still being optimized (e.g., low-resource NLP), enterprises have many considerations when using KMS to support real-time, relevant knowledge, and timely insights for distributed and diverse uses. This gap calls for lightweight, efficient models and scalable architectures—such as edge computing, streaming NLP pipelines, or continual learning methods—to ensure KMS can deliver timely, relevant knowledge insights across distributed environments.

D. Explainability and User Trust

While NLP models for organizational knowledge have become more accurate in their classification capabilities, researchers are pointing out that a gap still remains in the presentation of explainability in models and its implications on user trust (Ribeiro et al, 2016); (Doshi-Velez & Kim, 2017). Most deep learning models, especially Transformers, are "black box" models, and generally do not provide sufficient knowledge on how the classification is made. In high-risk environments such as health care, finance, or legal KMS, the opacity of black box algorithms is deterrent for use and raises concerns over accountability. Users and deciders of knowledge outputs need the information be transparent, and interpretable in order to trust and validate the automated categorization of knowledge. At present, explainability tools, such as LIME, SHAP, and others, are useful accounts of black box models but are still inadequate in the context of complex tasks under domain requirements. Researchers are calling for deeper integrated domain adaptive frameworks of explainability which align with organizational needs and user expectations.

E. Ethical and Bias Mitigation Frameworks

Researchers have pointed out that although NLP models provide a significant boost to the classification of knowledge, they often exacerbate existing biases found in the normal organizational text (Binns, 2018). However, not much in the way of ethical frameworks for KMS can be found. The ongoing work mainly focuses on technical performance without sufficient reassessment on fairness, accountability, and transparency in enterprise settings. Bias mitigation strategies like data debiasing, algorithmic auditing, or fairness-aware training have also not been implemented in KMS in practice. In fact, researchers have argued that ethical design principles and governance models must be incorporated into the development of and training using NLP classifiers in order to guarantee fair and responsible ways to manage knowledge generated by a diverse range of users in multiple fields and domains.

F. Integration with Existing KMS Infrastructure

Research has exposed notable disconnect in the current NLP-based text classification space that allows for integration into already-existing Knowledge Management Systems (KMS).

Although many of the NLP models that are available now tend to work separately well, implementing these models meant re-structuring the organization's existing systems or changing over existing data to use (Gelashvili-Luik et al., 2025).Most legacy KMS platforms do not have the modularity and/or APIs for modern NLP tools to be embedded. In addition, organizations' IT teams could face interoperability, performance, and maintainability issues with their models. This disconnect between NLP research and using it in organizations to improve the implementation of text classification, limits systems development and the value of text classification technologies to the real world. Academics stress a need for architectures that enables plug and play, middleware, or cloud-based APIs that support the flexible embedding of NLP capabilities into established, existing KMS environments.

G. Continuous Learning and Adaptation

Researchers have pointed out that most current NLP-text classification models used in KMS are trained in a static, one-time manner and struggle to adapt to evolving organizational knowledge and terminology (Parisi et al., 2019); (Chen et al, 2015). As businesses grow and generate new types of content, these models risk becoming outdated, leading to reduced accuracy and relevance in document classification. This is particularly problematic in dynamic environments such as healthcare, legal, or tech industries, where knowledge evolves rapidly. Despite progress in continual and lifelong learning techniques, their integration into enterprise KMS remains limited due to concerns over catastrophic forgetting, system complexity, and resource constraints. Researchers call for the development of adaptive NLP systems that can incrementally learn from new data while retaining prior knowledge, ensuring sustained performance over time without full retraining**.**

V. FUTURE DIRECTIONS

The incorporation of Natural Language Processing (NLP) text classification into Knowledge Management Systems (KMS) will continue to rapidly advance in accordance with technological developments and organizational demands. Indeed, researchers envision numerous potential future directions aimed at increasing the scalability, adaptability, interpretability and ethical compliance of NLP, and other NLP based KMSs, in enterprise settings.

A. Domain-Adaptive and Context-Aware Models

In the future, it is likely that KMS will utilize more domain-adaptive NLP models, and relevant datasets, to match the appropriate terminologies, writing styles, and semantics of differing professional fields. A study (Gururangan et al., 2020), discovered that by developing, and submitting, large language models (LLMs) to domain-specific corpora varying from medical, legal or scientific texts, the KMS classification of content yield improved accuracy and relevance. This transformation will allow organizations to design and use KMS for nuanced content with minimal time spent annotating by hand.

B. Multimodal Knowledge Classification

Alongside, the new area of multimodal knowledge classification where text is combined with other modalities like audio, video, and images. The importance of combining modalities to capture richer contexts, especially in knowledge-intensive fields like healthcare and education has been emphasized (Ahuja, Morency, & Baltrušaitis, 2019) KMS will use speech to text models, and image captioning methods that are offered alongside text classifiers, for creating inventories of transcripts from meetings, instructional videos, or scanned paper documents.

C. Real-time and Continuous Learning Systems

Organizations are demanding real-time insights and reporting, and this shift is pulling KMS towards streaming and real-time text classification systems. Edge computing is being leveraged in distributed NLP architectures and the connections between flexible state-of-the-art natural language processing (NLP) allows for higher quality recognition in terms of speed and agility in decision making for incoming knowledge objects (Méndez et al., 2022).

D. Explainability and Human-AI Collaboration

Explainability is becoming critical in enterprise KMS, especially where decisions affect policies, compliance, or customer engagement. Future NLP systems must provide transparent reasoning behind classification outputs. Techniques like Local Interpretable Model-agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP) (Ribeiro et al, 2016);(Lundberg & Lee, 2017) are increasingly being adopted. These methods help knowledge workers understand and trust AI recommendations, facilitating a collaborative human-AI decision-making process.

E. Ethical, Privacy-Preserving, and Fair Classification

Researchers emphasize that deploying NLP-based classification in KMS must be ethically responsible, privacy-conscious, and fair. The importance of explainable AI for transparency and accountability has been highlighted (Doshi-Velez & Kim, 2017). Shokri (Shokri & Shmatikov, 2015) advocate for privacy-preserving methods like federated learning to protect sensitive organizational data. To address fairness, Mehrabi (Mehrabi et al., 2021)stress the need for bias audits and inclusive training data to prevent discrimination and ensure equitable classification outcomes. These approaches collectively support the trustworthy and responsible use of NLP in enterprise knowledge systems.

VI. CONCLUSION

Researchers agree that integrating NLP-based text classification into Knowledge Management Systems (KMS) significantly enhances the efficiency, scalability, and intelligence of organizational knowledge handling. It enables automated categorization, improved information retrieval, and better decision-making across domains such as

healthcare, finance, and education. Classical machine learning models like Naïve Bayes and SVMs laid the groundwork, while modern deep learning methods—especially Transformers like BERT—have dramatically improved accuracy and contextual understanding. However, challenges remain in areas such as explainability, ethical fairness, real-time adaptation, and seamless integration with existing systems. Scholars emphasize the need for domain-specific adaptation, user trust, and continuous learning frameworks to maximize the long-term utility and responsible use of NLP in KMS. As such, future research must bridge technical advances with organizational realities to create robust, ethical, and scalable knowledge management (KM) solutions.

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