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THE ROLE OF MACHINE LEARNING IN AUTOMATED CODE CHECKING – A SYSTEMATIC LITERATURE REVIEW

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SUMMARY: *Building design must adhere to numerous codes, laws, and regulations. In practice, despite the available tools for Automated Code Checking (ACC) and the extensive research in the field, checking whether a given design complies with all relevant regulatory requirements remains a manual and time-consuming task. A comprehensive checking system that provides highly automated solutions for a wide range of regulations remains a distant goal. Recent studies have underscored the potential of engaging advanced technologies like Machine Learning (ML) and Natural Language Processing (NLP) to enhance ACC abilities. Hence, this work aims to review recent advancements in implementing ML technologies in code compliance checking, identify knowledge gaps, and suggest future research directions. By implementing a systematic literature review methodology, we identify three key research areas within the domain: processing regulatory text, processing design information, and an overall checking mechanism. Existing efforts explore each of these areas using a variety of ML algorithms to enhance their effectiveness. Despite the notable advancements, challenges persist due to the complexity of regulations, ambiguity of legal texts, and the scarcity of training data, all of which limit the scalability of the presented approaches. Additionally, while ML enhances flexibility by learning from data rather than relying on hardcoded rules, it introduces uncertainties in decision-making processes critical to building permitting. The review highlights the potential for hybrid approaches that combine the strengths of both rule-based systems and ML models to effectively address these challenges.*

KEYWORDS: *Automated Code Compliance, Machine Learning (ML), Rule-based checking, Building Information Modeling (BIM).*

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1. INTRODUCTION

Traditionally, code compliance checking has been a manual process carried out by domain experts, such as designers, authorities, and other stakeholders. This process relies heavily on their interpretations of the regulations and the designs (Dimyadi and Amor 2013a). However it is inherently complex, error- prone, and leading to low productivity due to its labor-intensive nature (Preidel and Borrmann 2018). The drive to automate design review has been at the forefront of research since the 1960s (Fenves 1966), and it remains an active field of research today. We consider Automated Code Checking as the process of verifying building design documents against regulatory requirements in a systematic and automated manner. This Process involves two main aspects; the design itself and the regulations governing it. In the context of automation, the goal is to achieve a computer-readable representation of both, facilitating direct comparison without further mappings or interpretations (Bloch et al. 2023). One of the main challenges is that the concepts represented in these two data sources often do not align. The ability to bring the regulations and the design to a common environment and representation is the motivation of many of the recent research efforts (Amor and Dimyadi 2021).

A common approach to ACC is to interpret the regulatory documents and translate the text into rules which can consequently be hardcoded into the checking system. The four-stage process suggested by (Eastman et al. 2009) which includes rule interpretation, design preprocessing, rule implementation, and report, is the backbone of the most advanced ACC application such as Solibri (Solibri 2017). Solibri provides an extensive library of rules that are customizable to some extent and offers sophisticated checking functionalities. One of the drawbacks of the platform (as well as other ACC platforms) is that it implements a "black box" procedure. Namely, the rules are not "human readable", and the internal logic is not entirely transparent to the user. Customization of the rule sets presents significant challenges, demanding not only extensive coding expertise but also requiring close collaboration with the software vendor to implement any proposed modifications.

To overcome some of these limitations Dimyadi and Amor (2013b) proposed representing regulations using the open standard LegalRuleML, while utilizing Business Process Model and Notation (BPMN) to represent specific compliance checks. Similar method was also implemented for checking compliance of railway design (Häußler et al. 2021). Preidel and Borrmann (2016) proposed the Visual Code Checking Language (VCCL), which uses a graphical notation to represent building codes in a machine-readable and human-readable format. Such visual methods for representing regulations make the code checking process accessible to domain experts with limited programming knowledge.

For interpretation of regulatory documents Numerous methods have been examined and employed. For example, RASE (Requirement, Applicability, Selection, and Exception) is a markup technique (Hjelseth and Nisbet 2011; Nisbet et al. 2022) that aims to transform documents into well-defined rules. Implementation of RASE has been tested for regulatory documents and reliable results have been illustrated (Hjelseth and Nisbet 2011). Zhang and El-Gohary (2016b) presented a methodology for using rule based NLP for automated information extraction from regulatory documents. This method relies on a set of manually coded rules for text processing. Although this method yields accurate processing results, it involves much manual work. Despite the accuracy of such rule-based methods, they lack the flexibility often required in ACC procedures (Li et al. 2016; Zhou and El-Gohary 2017). Rules are typically designed to handle clear, well-defined conditions. However, regulatory documents are complex and often contain ambiguous or vague language which poses significant challenges for rule-based systems. Based on the work of Zhang et al. (2023) there are several types of ambiguity in regulatory documents, some is intentional ambiguity (such as performance-based regulations), but some is unintentional and stem from the use of natural language. For example, vagueness is a type of ambiguity that can result from poor use of language. Lexical ambiguity can occur when using phrases with multiple meanings. Incompleteness is when information is missing from the regulatory provisions. This may explain why existing automated rule interpretation methods primarily focus on simpler regulatory sentences as more complex and extensive requirements would greatly challenge the rule-based systems (Zhou et al. 2022b).

Recent work, like that of Kruiper et al. (2024), proposed a more flexible and dynamic approach using NLP combined with Semantic Web technologies and ML. This approach leverages NLP tools to handle challenges like ambiguous language, inconsistent use of terms, and multi-word expressions by enriching the regulatory text semantically and structuring it into machine-readable formats. In addition, the integration of knowledge graphs helps in resolving ambiguities by linking regulatory terms to predefined vocabularies, improving accuracy and retrieval during compliance checking. While the primary focus is on NLP and Semantic Web methods, the inclusion of ML allows for further optimization in processing complex regulatory documents, providing a more robust solution for automated compliance checking. We can therefore see potential for ML in handling complex regulations. Wang and El-Gohary (2023b) highlight the promise of deep learning techniques in resolving referential ambiguities, indicating that ML could be instrumental in overcoming these challenges, though its full potential is still under exploration. One of the strengths of ML is its ability to learn from annotated examples where human experts have interpreted the regulations. ML models aim to mimic aspects of human decision-making by learning patterns from data and applying them to new, unseen cases. ML models rely on data-driven processes rather than human-like reasoning. They generalize by identifying underlying patterns in the training data, allowing them to adapt to various inputs (Zhang and El-Gohary 2020a). That said, the lack of sufficient training data presents a significant barrier to achieving accurate results with ML (Zhong et al. 2020). A more balanced perspective emphasizes the importance of understanding the benefits and challenges of ML-based methods compared to rule-based methods, especially when dealing with complex requirements (Zhang and El-Gohary 2022a).

In terms of design representation, Building Information Modeling (BIM) is one of the driving technologies behind the efforts to automate code checking. BIM has reshaped construction project delivery, affecting every stage in the project's lifecycle and offering numerous possibilities for automation (Sacks et al. 2018). Introduction of the Industry Foundation Classes (IFC) schema to facilitate effective data exchange between platforms introduced even more opportunities for advanced applications such as code compliance checking. One significant and persisting issue is ensuring that the models contain sufficient and accurate information to support comprehensive code checking. The completeness and standardization of BIM data are critical for the effective application of rules, as inconsistencies or gaps in the data can lead to errors in the compliance checking process (Jiang et al. 2022).

Information provided in BIM models is often not sufficiently rich for advanced applications such as code checking. One notable project is Singapore's CORENET where semantic extensions of BIM were developed and collected into a library called FORNAX (Solihin et al. 2004). Many other researchers proposed the idea of enriching BIM models to support ACC (Bloch and Sacks 2018) or extending BIMs with regulatory concepts (Solihin and Eastman 2016). For example, Zhang and El-Gohary (2014) integrated NLP and ML to enrich the IFC schema with regulatory concepts, and later introduced a semi-automated technique for classifying relationships within the IFC to better incorporate regulatory concepts into the BIM based checking process (Zhang and El-Gohary 2016a).

While the aforementioned work focused on the STEP representation of the design, some efforts adopted web technologies as a base for reasoning over design information (Pauwels and Zhang 2015) and as a base for enriching the BIM models (Werbrouck et al. 2020). Semantic enrichment heavily relies on the ability to query BIM models for which many approaches have been developed (Borrmann et al. 2006; Borrmann and Rank 2009; Daum and Borrmann 2013; Mazairac and Beetz 2013; Wülfing et al. 2014; Zhang et al. 2018). Advanced methods like semantic enrichment and ontology-based reasoning show promise in addressing the semantic inconsistencies between BIM data and predefined rules (Jiang et al. 2022). Recently, approaches to semantic enrichment extended beyond logical inferencing and the abilities of ML models have been illustrated to automatically infer and supplement required information into the BIM models (Bloch and Sacks 2020; Koo et al. 2019; Wang et al. 2022).

The need for specific, well defined, and quality information for ACC is clear. At the core of automated code checking, regardless of the specific approach employed, lies a fundamental and unifying element—information requirements. They form the bridge between design representations and regulatory documents, enabling comparison between the two which is fundamental for ACC. Unfortunately, despite the research efforts, the approach of supplementing the needed information manually prevails. Amongst the recent advances in this domain, is the introduction of the Information Delivery Specifications (IDS) which is a standard in development by BuildingSmart (2024) aiming to define information requirements in a way that is both readable to humans and machines. While this will enable automatically checking that all information requirements are met prior to the design review, the effort to supplement all required information in the defined representation will fall on the designers and modelers. In other words, the manual efforts will simply shift from the actual checking process to the process of creating a BIM model to be checked (Amor and Dimyadi 2021).

In the continuous evolution of ACC, diverse methodologies have been proposed, and a shift towards more sophisticated techniques is evident. With the major transformation that ML introduced to the construction domain, it is not surprising to see ML implementations in the ACC domain as well. The integration of ML with BIM presents new possibilities for ACC and offers the potential to overcome some of the limitations in the existing workflows. We aim to investigate where these fields intersect, assessing recent advancements, identifying research gaps, and pinpointing unexplored topics that need to be further investigated.

The drawbacks of traditional ACC workflows have been recognized in previous work and discussed in existing review papers on the subject, which are mainly focused on rule based methods (Amor and Dimyadi 2021; Dimyadi and Amor 2013a; Ismail et al. 2017). Despite years of research and many notable efforts, we have not seen a significant breakthrough in the field. With the many proven possible applications of AI across various domains in AEC, researchers have begun exploring ML as a potential game-changer for ACC. While ML holds promise in dealing with some of the existing challenges, there is a notable gap in the literature regarding our understanding of what has been achieved so far with ML in ACC, and what are the critical challenges that remain. This work aims to address this gap through a comprehensive literature review.

To the best of the author's knowledge, there are currently no comprehensive reviews on the application of ML to ACC. To fully harness the potential of ML application to ACC, it is crucial to map out the current landscape of ML methods in this field, to understand what has been done, what are the existing gaps in knowledge, inconsistencies in approaches, and opportunities for future research. Through a careful review and analysis of existing literature, our goal is to uncover the trends, successes, and gaps in using ML for code checking. Additionally, this review will enable us to highlight the key challenges and limitations that researchers have encountered in ACC using ML and to shed light on promising directions for future research. Through this exploration, we aim to provide a structured understanding of the existing state of the art, opportunities and challenges, and outline the work that still needs to be done in order to potentially lead to significant advancements.

2. METHODOLOGY

In this work, we adopt the systematic literature review methodology. The first stage of this methodology is formulating a well-defined research question to guide the process. Then, a search strategy is defined to identify the relevant studies. Once the search is implemented on chosen reputable academic databases, a screening process focusing on assessing abstracts is performed, followed by the full text review and analysis. The findings are then summarized and interpreted, and meaningful conclusions are drawn (Khan et al. 2003). This methodology ensures a comprehensive and unbiased exploration of the subject, contributing to a robust understanding of the current state of knowledge in the field.

2.1 Research questions

As explained in the introduction section, in recent years, significant advancements have been made in the field of code checking, with various advanced approaches being implemented. To make progress in the ACC domain, it is essential to gain an in-depth understanding of these different methods and identify where they can be most beneficial in the checking process. To do so, we propose a bottom-up approach, starting with a thorough investigation of each of the methods individually. As the rule-based approach for ACC has been thoroughly investigated over the years, we turn to address the ML approach in the ACC context. This work aims to explore the current landscape, achievements, and challenges concerning the integration of ML for automated code checking. Within this overall goal, we aim to answer the following questions:

RQ 1 - How have ML-based approaches been applied before to enhance automated code checking processes?

RQ 2 - What are the existing challenges and opportunities in integrating ML solutions with ACC, and how have researchers addressed these challenges?

RQ 3 - What are the research gaps in the literature, and what are the most promising future research directions?

2.2 Search strategy and literature evaluation

The chosen data source for conducting this research was Scopus, which is a large data set that provides wide coverage of scientific literature in the AEC domain (Mongeon and Paul-Hus 2016). The overall methodology for identifying scientific publications is illustrated in Figure 1. The advanced search tool in Scopus was used to identify relevant publications. The search was performed using the following key: TITLE-ABS-KEY (("code conformance" OR "code checking" OR "compliance checking" OR "code compliance") AND ("machine learning"

OR "ML" OR "deep learning" OR "NLP" OR "Natural language processing")). This initially led to 126 documents. Excluding publications from irrelevant domains led to a final set of 95 relevant documents. The search was not limited by date, and conference papers were not excluded.

The abstracts of all identified publications were read and analyzed to ensure the relevance and quality of the studies. The abstract screening process is a critical step in the methodology to ensure that only relevant publications are included in the final analysis. Two main criteria were evaluated during the abstract reading:

1. Relevance to ACC: The publication must specifically address aspects of automated code checking of building design. For example, some of the identified papers referred to conformance to onsite work regulations, like safety standards, fall protection measures etc. Such publications were filtered out during abstract reading.
2. Application of ML: The publications must involve the application of ML techniques, including deep learning, NLP or other related methodologies. Some of the identified publications presented conceptual ideas for the use of ML for ACC as part of the paper, therefore the author keywords included “ML” or other relevant concepts. However, the focus of these publications was not ML for ACC, and they did not describe a ML application in this context. Such publications were filtered out during abstract reading as well.

During abstract reading, it became clear that the publications contain several underlying topics suitable for in depth analysis. Therefore, the final step in the search and evaluation strategy is the classification of all relevant publications (a total of 71 publications identified during abstract screening) based on their underlying topics. This classification process involved identifying key themes and categorizing the publications, based on screening the full papers. Each publication was examined primarily by focusing on its aims and objectives to understand its primary research focus. Once all papers were classified, an in-depth read and analysis was performed. The results of this thorough analysis are presented in the following section.

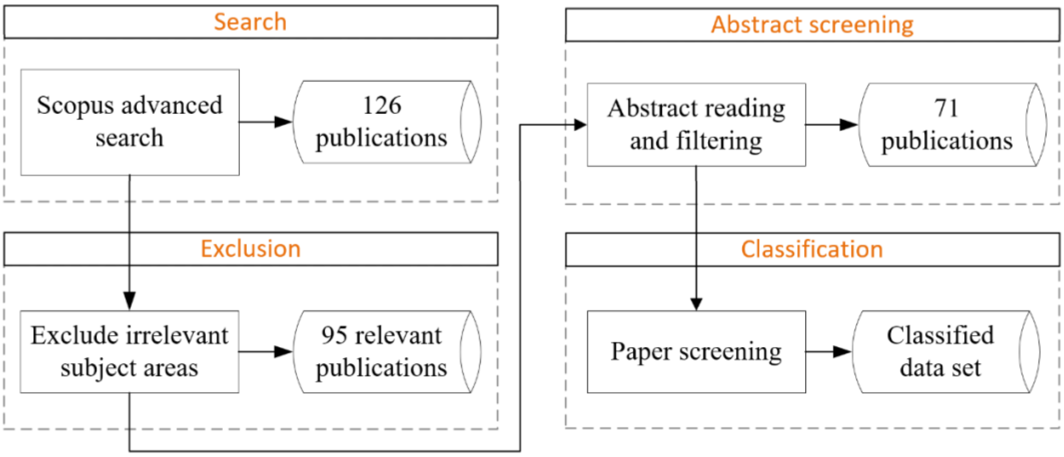

Figure 1: Search methodology.

The described methodology provides a structured process that allows us to answer the presented research questions. The research strategy allows us to identify and analyze a wide range of papers describing the application of ML to the ACC process. This analysis will provide a comprehensive overview of previously implemented ML methods and their potential in enhancing ACC (RQ1). Furthermore, the classification of identified papers allows us to understand the distinct potential of ML applications for two of the main challenges in the process – rule interpretation and design information preprocessing. Analysis of papers based on their thematic categories can pinpoint opportunities and challenges specific to different steps of the ACC process. ACC relies on two different sources and types of information (regulatory text and design). Therefore, implemented methods, challenges, opportunities, and employed strategies (RQ2) might be different in different steps of the process. Through analysis of relevant publications, we will identify consistent gaps in the field (RQ3). By classifying the relevant papers, the review will highlight underexplored areas, recurring limitations, and potential avenues for future research.

3. RESULTS AND FINDINGS

As explained in the methodology section, the abstract screening revealed that each publication addresses different challenges or stages within the ACC workflow. The first group of publications focuses on the regulations and addresses the challenge of interpreting regulatory requirements and converting them into computable statements. The second group is focused on design information. Publications in this category deal with preprocessing and enriching BIM models to prepare them for the checking process. The publications in the third group look at the checking process overall. This information was documented during the abstract screening process and evaluated again during screening of the full papers. The list of the reviewed publications, classified into the three groups, is presented in Table 1.

Notably, a significant portion of the existing publications primarily focus on transforming regulatory documents into machine-readable representations. As demonstrated in Table 1, over 60% of the reviewed publications discuss the use of ML for interpreting regulatory requirements.

However, as illustrated in Figure 3, the tide seems to be slowly changing, as recent efforts begin to emerge, showing promise in exploring ML's applicability and potential for preprocessing the design and for transforming the code compliance checking process overall. The rising interest in the subject in the last two years is also evident, with 29 papers published during 2022-2024.

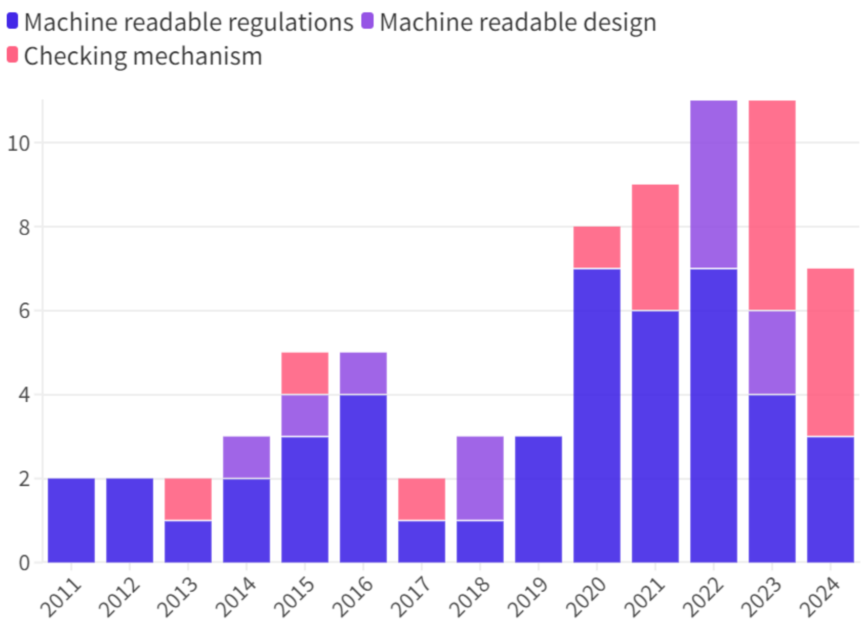

Figure 3: Year of publication for the papers in each of the classes.

Table 1: Classification of relevant publcations.

Class	References
Machine readable regulations	(Fuchs et al. 2022, 2023; Kruiper et al. 2021, 2024; Li et al. 2020; Purushotham et al. 2024; Salama and El-Gohary 2013, 2011a; b, 2016; Schönfelder and König 2021; Uhm et al. 2015; Wang and El-Gohary 2022, 2023a; b; Xu et al. 2019, 2020; Xu and Cai 2021; Xue et al. 2024; Xue and Zhang 2020a; b, 2021, 2022; Zhang 2023; Zhang and El-Gohary 2012a; b, 2015b, 2016b, 2019a; b, 2020a; b, 2021, 2022a; b, 2018; Zhou and El-Gohary 2014a; b, 2015, 2016a; b, 2017; Zhou et al. 2022a; b)
Machine readable design	(Bloch and Sacks 2018; Dinis et al. 2022; Fei et al. 2022; Karmakar and Delhi 2024; Koo and Shin 2018; Luo et al. 2023; Wu et al. 2022; Zhang and El-Gohary 2016a, 2014, 2015a; Zheng et al. 2022)
Checking mechanism	(Bloch et al. 2023, 2024; Chen et al. 2024; Guo et al. 2021; Li et al. 2024a; b; Li and Cai 2015; Locatelli et al. 2021; Peng and Liu 2023; Wang and El-Gohary 2024; Wang et al. 2023; Zhang and El-Gohary 2013, 2017, 2020c, 2023; Zhou and El-Gohary 2021)

3.1 Computer readable representation of the regulations

Many efforts have been focused on developing automated code compliance systems, but their use remains limited due to the need for extensive human input to convert building codes into computer-readable format. Various text classification approaches have been explored to automatically interpret regulations. Some work focuses on the automated classification of documents to predefined classes in preparation for further analysis and rule extraction for ACC. For example, Salama and El-Gohary (2016) suggested a hybrid approach for classifying clauses using a text classification technique that implements a semantic model and a ML model. A ML approach for text classification was also implemented for classifying environmental regulatory clauses using several popular ML algorithms like Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes (NB), Nearest Neighbors (NN), and Ensemble Method (Zhou and El-Gohary 2014a).

Natural Language Processing (NLP) plays a pivotal role in the processing of regulations, and it has been widely investigated in the context of ACC. For example, Zhang and El-Gohary (2012a; b) explored the effectiveness of utilizing syntactic and semantic features of the text to automatically extract regulatory information from codes. Portions of the International Building Code and the International Fire Code were used to demonstrate the proposed approach, showing promising results with 95% precision and 94% recall. A similar information extraction technique was implemented for extracting regulatory requirements from the International Energy Conservation Code and also demonstrated promising results (Zhou and El-Gohary 2017). Another integral part of NLP is the Part Of Speech (POS) tagging, where each word in a sentence is assigned a specific part-of-speech tag (noun, verb, adjective, etc.) which is crucial for understanding the grammatical structure of a sentence. The proposed algorithm was tested in extracting energy requirements from Chapter four of the 2012 International Energy Conservation Code, and the results showed 98.5% precision and 97.4% recall. Xue and Zhang (2021) suggested a novel approach, combining deep learning models with error-fixing transformational rules, to improve the accuracy of the existing POS taggers on building codes. Although their work demonstrated enhanced performance, the resulting POS tagger still contains errors, which could affect the performance of the entire NLP based code checking system. The proposed model reached a 91.89% precision without error-driven transformational rules and a 95.11% precision with error-driven transformational rules, which outperformed the 89.82% precision achieved by the state-of-the-art POS taggers.

To support ACC there is a need not only to extract concepts from the regulatory document but also to transform them into logical statements. Such a transformation method was proposed in the work of Zhang and El-Gohary (2015b). Their approach begins with a rule based, semantic NLP approach and rule-based information extraction. Then, the extracted information instances are transformed into logical clauses using a set of pattern-matching-based rules. Results of implementation for chapter 19 from the International Building Code (IBC) were compared to a manual rule extraction and showed precision and recall over 98%. However, this approach was only implemented on quantitative requirements and was affected by six different causes of errors. The information extraction technique was further improved by Zhou and El-Gohary (2016a) who proposed a supervised ML multilabel text classification algorithm to classify regulatory clauses prior to information extraction. Four types of multilabel classification evaluation metrics were used to measure the performance of the proposed approach. Based on the testing data, across the four types of metrics, the proposed algorithm achieved overall recall and precision values from 97.32 to 98.69% and from 86.51 to 92.70%, respectively.

A critical step in this information extraction process involves identifying key terms that convey semantic information in each design rule. Named Entity Recognition (NER), a sub-task in NLP, focuses on identifying these entities in unstructured text and assigning them labels based on predefined classes. Schönfelder and König (2021) proposed a supervised deep learning transformer model to extract relevant terms from German regulatory documents. Their method achieved weighted performance scores of over 95% precision and 95% recall. However, further investigation is needed to explore whether the proposed model outperforms rule-based approaches. In addition, extraction of concepts from the regulatory documents is not sufficient to support ACC, and the complex task of extracting the semantic relations between entities must be addressed as well. In an attempt to do so, Li et al. (2020) proposed a joint extraction model using a hybrid deep learning algorithm with a decomposition strategy and demonstrated it using the Chinese code to extract multiple relations. The proposed model achieved an average precision, recall, and F-1 measure of 88.08%, 85.19%, and 86.61%, respectively. Although the proposed approach showed potential, limited entity and relationship types were addressed.

In another effort by Wang and El-Gohary (2022) two alternative deep learning models, a CNN-based model and an RNN-based model, were developed and evaluated for extracting domain-specific relations from construction safety regulations. In this case, the CNN model achieved a weighted precision, recall, and F-1 measure of 82.7%, 81.1%, and 81.3%, respectively. Still, the identified relationships are most likely not exhaustive. One of the contributions of their work is that the presented approach has the capability to directly produce a structured representation for the extracted requirements as a query-graph. This structure further facilitates the identification of implicit information through edge traversal.

To address semantic parsing's early stages, Kruiper et al. (2021) introduced SPaR, a shallow parsing approach for ACC. Using a small dataset of 200 sentences, they developed a sequence tagging model that achieved an F1-score of 79.93% in identifying terms from Scottish Building Regulations. The approach focused on term recognition but was limited by challenges with complex multi-word expressions and dataset scalability. Building on this, Fuchs et al. (2022) advanced the field by developing a neural semantic parser for extracting building regulations using LegalRuleML (LRML). Their methodology translated natural language regulatory clauses into machine-interpretable format, improving parsing performance. Through data augmentation and normalization, they enhanced BLEU scores from 36.8% to 60.7% and format-specific F1 scores from 35.0% to 48.0%. Despite significant progress, challenges remain in maintaining annotation consistency and handling complex regulatory clauses.

Not all regulatory requirements can be interpreted automatically, some are too complex and require human comprehension. To gain some insights of the computability of different code requirements, Zhang and El-Gohary (2018) proposed a clustering approach to identify different types of code requirements in terms of computability. To enable analysis of the complex requirements (such as requirements with multiple nested clauses), researchers proposed the use of sentence and document templates. Zhang and El-Gohary (2019a) even suggested an automated approach based on unsupervised ML for such template extraction. The achieved accuracy for the final set of templates was promising but limited and stood at 76%. A machine learning-based method to automatically extract hierarchies of such complex requirements was also explored and achieved a precision of 89%, a recall of 76%, and an F1-measure of 82% (Zhang and El-Gohary 2019b).

Information extraction from regulatory documents is a challenging task that has been tackled with variety of methods, including deep learning (Zhang and El-Gohary 2020b, 2021, 2022a) and transfer learning (Zhang and El-Gohary 2020a). Zhang and El-Gohary (2020a) proposed transfer learning techniques to train a deep neural network for generating semantically-enriched building-code sentences for semantic analysis of the code for supporting automated compliance checking. These efforts contribute to the development of more scalable, flexible, and intelligent ACC systems, showcasing the potential of ML in improving interpretation of regulatory documents.

Whether dealing with regulatory compliance, building codes, contractual documents (Salama and El-Gohary 2011a; b), or other construction documents like requests for proposals (Uhm et al. 2015), common challenges in automating compliance checks persist. Amongst these challenges are the complexity of translating requirements into computer-interpretable rules, ambiguity, inconsistency, and the variability of construction projects. ML emerges as a promising direction to enhance automation, streamline the analysis of diverse documents, and facilitate the translation of complex requirements into computationally interpretable rules.

3.2 Computer readable representation of the design

Two critical aspects need to be considered to enable automation in the code checking process: accurate interpretation of regulatory documents, and availability of high-quality, semantically rich design data, both in machine-readable formats. Despite the widespread adoption of BIM, challenges in rendering machine-readable design information persist and may hinder the adoption of ACC in practice. Ensuring the accuracy, completeness, and consistency of design data is fundamental to the success of any ACC system. The papers reviewed in this section present ML applications to tackle these issues. Karmakar and Delhi (2024) examined the obstacles in implementing ACC systems in the Indian construction industry. Their focus was on understanding the practical considerations in application of ACC systems, especially in pre-construction permit compliance. Through a focus group study, they identified key challenges such as manual data preprocessing of BIM Models and the limited scope of the code checking system that focuses on only explicit and simple building code clauses. The research highlighted the need for automated data preprocessing, including intelligent model filling and semantic enrichment. They also propose the use of ML for automatic semantic enrichment, aiming to improve the industry's adaptation and user experience of ACC systems.

The use of a variety of software packages in the AEC industry necessitates effective information sharing between the stakeholders. The IFC schema was designed to facilitate such information exchange, which is at the core of the existing ACC platforms as well. BIM based ACC requires accurate and rich semantic information to be explicitly expressed in the IFC. Semantic enrichment of BIM models is a process aiming to supplement the missing information automatically to enable an ACC process. Bloch and Sacks (2018) proposed the use of ML algorithms for semantic enrichment of BIM models and compared them with rule-based approaches for space classification. Since accurate information about the functionality of spaces in a building is at the heart of many regulatory requirements, automatically supplementing this information would support a range of regulatory compliance checks. Their experiments demonstrated the superiority of ML in correctly identifying spaces within apartments, as opposed to rule-inferencing, which proved less effective due to the absence of unique distinguishing geometric features. However, the ability to implement such methods is dependent upon the availability of a large, labeled, data set of design variations. Generalizability is an issue as well since the proposed method was demonstrated for classification of functional spaces in residential apartments, the applicability for other building types has not been explored.

Missing information is not the only limitation of BIM based ACC, as existing information may be misrepresented or incorrectly mapped into the IFC representation (Koo et al. 2021; Lai and Deng 2018; Pazlar and Turk 2008). Addressing possible mapping errors between BIM native models and IFC representations, Koo and Shin (2018) applied Support Vector Machine (SVM) to accurately identify such misclassifications. The proposed approach aimed to ensure accurate BIM - IFC class mappings for seamless data exchange, which is another important preprocessing step for ACC. Their work highlighted the need for model integrity checks. In this case as well, limitations around generalizability to different building types were noted.

Expanding on classification tasks, Wu et al. (2022) introduced a method for classifying AEC objects in BIM using invariant signatures that encapsulate geometric, locational, and metadata aspects. Their research showed that invariant signatures, coupled with the random forest algorithm, achieved remarkable object classification accuracy (99.6% F1 measure). This approach holds promise for various BIM applications, including cost estimation, automated code compliance checking, energy analysis, etc. However, as in the previously mentioned efforts, large datasets are needed for implementation.

Dinis et al. (2022) offered a more comprehensive perspective on semantic enrichment by reviewing semantic enrichment methods for BIM, addressing the challenges of data integration, manual modeling updates, and interoperability constraints. They illustrated a wide range of semantic enrichment techniques, including ML algorithms, ontology-based systems, and semantic web technologies. By categorizing research efforts into specific BIM-related use cases, one of which is ACC, they highlighted the potential of semantic enrichment to support code checking.

While most of the work on semantic enrichment relies on the properties of individual elements, relational information is of great value in the context of building design information. In an effort to leverage such relational information, Luo et al. (2022) introduce two-branch geometric-relational deep learning framework for BIM object classification. The framework was comprised of two synergistic branches: a geometric branch that extracts high-level features from the shape information of BIM objects, and a relational branch that processes relational data to learn the interaction patterns among objects within their BIM context. Despite demonstrating improved classification accuracy and flexibility, the authors acknowledged certain challenges. These include issues related to potential mislabeling, loss of relational data in IFC files, the necessity for more comprehensive datasets to encompass a wider array of BIM objects and relationships, and the existing coarse definitions of BIM object types that may limit detailed domain-specific applications.

In the context of ACC, enriching BIM models goes beyond just adding semantic information; it's about ensuring that the design information aligns with the regulatory documents. This alignment is crucial to enable automated checking workflows. In 2016, Zhang and El-Gohary (2016a) suggested another semi-automated technique to extend IFC using machine learning for relationship classification, aiming to more efficiently incorporate regulatory concepts into BIM-based ACC. Their method matched document concepts to IFC entities and classified the relationships using syntactic, semantic and machine learning techniques. Four main ML algorithms were tested, and the best performing algorithm achieved 88.2% precision. Following this, Zhang and El-Gohary (2016c) expanded on their work with a comprehensive approach that combines concept extraction, matching and classifying relationships to semi-automatically extend BIM with regulatory concepts. Their approach demonstrated 87.9% precision and 91.7% F1-measure, illustrating the potential to improve ACC workflows. A major limitation of these significant contributions is that the methods were tested on a limited scope of regulatory documents, hence additional testing is needed to examine scalability and handle more complex requirements. In addition, the ability to evaluate the results of these methods is dependent on developing a benchmark against which testing results can be compared, which requires extensive manual work.

More recently Zheng et al. (2022) proposed an innovative knowledge-informed automated rule checking framework comprising four key components: ontology-based knowledge modeling, semantic enrichment, enhanced rule interpretation, and checking execution. They established a domain-specific ontology to represent critical domain knowledge, improving the generalization of alignment between regulatory concepts and design concepts. Their unsupervised semantic alignment method achieved an impressive 90.1% accuracy rate, reducing manual effort, and enhancing alignment accuracy. The authors emphasized knowledge-informed conflict resolution and introduced a domain-specific text classification method for rule interpretation. The framework was demonstrated in a prototype system using open-source tools. However, like previous efforts, the presented ontology and rule sets were focused on a narrow set of standards. Wider applicability across regulatory domains has not been explored. Additionally, the presented framework did not encompass parsing IFC files, a significant barrier to real-world engineering implementations.

It is obvious that despite recent advancements, some challenges in the field persist, including the need for extensive efforts for BIM preprocessing and limited coverage of regulatory scope (Zhang and El-Gohary 2016a, 2014, 2015a; Zheng et al. 2022). The reviewed publications underline the need for future work to enhance the scalability, precision, and applicability of ML for ACC systems. Future research must focus on broadening the scope of regulatory document testing, exploring more sophisticated ML techniques, and developing more diverse datasets.

3.3 Checking mechanism

As the industry still heavily relies on document-based information sharing and management, NLP is a potential solution to process such unstructured data effectively. Locatelli et al. (2021) illustrate the close relationship between NLP, BIM, and semantic topics, with NLP acting as a bridge between document-centric and information-based approaches. Similarly, NLP can serve as a bridge between the regulatory documents and the design information to facilitate an automated compliance check. In this section, we review the publications that focus on bridging this gap and publications that illustrate a complete checking workflow that includes both processing of the regulatory text and of the design.

Researchers have been actively exploring innovative approaches to streamline and enhance the ACC process, with a focus on bridging the gap between regulatory textual requirements and digital building model representations. One such approach was introduced by Zhang and El-Gohary (2013), where semantic modeling, semantic NLP techniques, and logic reasoning were combined for processing of textual regulatory documents. To extract and formalize requirements into a computer-readable format, they relied on a set of integrated algorithms, including semantic machine-learning-based algorithms for text classification (TC), syntactic-semantic rule-based algorithms for information extraction (IE), semantic rule-based algorithms for information transformation (ITr), and logic-based algorithms for compliance reasoning (CR). The combined TC, IE, and ITr algorithms were successfully tested for extracting and formalizing quantitative requirements from the 2006 International Building Code, achieving high precision and recall rates of 96% and 92%, respectively.

Li and Cai (2015) introduced a framework that addresses recurrent underground utility incidents. These incidents are often caused by non-compliance with spatial rules specified in utility documents and a lack of awareness regarding utility locations. Li and Cai (2015) implemented an NLP algorithm to extract spatial rules from textual utility documents and convert them into a computer-interpretable format. Using spatial reasoning, they interpreted spatial relationships from utility documents such as positioning, direction, and distance, into actionable rules. These rules were then applied in a Geographic Information System (GIS) to automate the depth estimation of underground utilities and verify their compliance with regulations. Wang et al. (2023) also leveraged NLP techniques, for fire code compliance checking. Their proposed framework comprises three key subtasks: building model parsing, code knowledge translation, and compliance check result. They introduced a structured NLP approach to process spatial geometric stipulations in fire codes, enabling the review of component relationships within building models. Empirical testing demonstrated the system's ability to achieve superior recall compared to manually formulated gold standards. However, it has some limitations, particularly in expanding logical expressions to cover a broader range of codes. There is also room for extending the approach to different building types.

Locatelli et al. (2021) and Wang et al. (2023) highlight the ongoing challenge of translating complex, often ambiguous regulatory texts into computable formats that accurately reflect the intent and applicability of the regulations. Furthermore, as discussed in Peng and Liu (2023), reliance on NLP to transform specifications into checking rules raises concerns about the accuracy and reliability of rule generation. Natural language's inherent ambiguity and complexity can pose significant challenges in accurately capturing the code requirements, potentially leading to oversimplifications or misinterpretations in the automated rules.

Zhang and El-Gohary (2020c) continued to refine ACC methodologies by proposing a ML-based approach for semantic matching between building codes and BIM models. Their approach focused on three key components: the generation of semantic representations that blend domain-specific and general word embeddings, a similarity-based method for matching building-code concepts to IFC elements, and a supervised learning-based approach for matching building-code relations to IFC relations. The preliminary results show that the proposed approach achieved an accuracy of 77% for matching building-code concepts to IFC elements, and 78% for matching building-code relations to IFC relations. One of the primary contributions lies in their methodology for modeling semantic meanings within domain-specific text. By combining domain-specific word embeddings with general word embeddings, their approach harnessed both domain-specific knowledge and broader semantic context. They illustrate how the system discerns the semantic depth behind the term 'Horizontal sliding power-operated door' found in building codes and aligns it with the 'IfcDoor' entity. In this case, the 'Horizontal sliding power-operated door' was also recognized as a subtype of the broader 'IfcDoor' category. Recognizing that the detailed descriptor 'Horizontal sliding power-operated' enriches the base concept of 'door' with specific functional attributes, allows the system to identify it as a particular kind of 'IfcDoor'. The successful experiment demonstrated the capability to accurately capture the semantic complexities embedded within building-code concepts and deduce their relationships to IFC elements. Despite the benefits, the reliance on domain-specific embeddings indicates the importance of creation and maintenance of extensive domain-specific knowledge bases. This dependency raises questions about the flexibility and adaptability of such systems to new codes and regulations without extensive retraining or updating of embeddings.

Zhang and El-Gohary (2023) introduced another approach for automated IFC-regulation semantic information alignment. This method leveraged transformer-based models to establish connections between regulatory concepts and the concepts within the IFC schema. To enhance alignment accuracy, the authors incorporated natural-language definitions and an IFC knowledge graph, providing contextual information for fine-tuning a pretrained transformer-based model through transfer learning. The approach achieved an average precision of 84.3%, recall of 83.3%, and an F1 measure of 83.8% in concept alignment. The results highlight the method's limitations in fully capturing the complexity of regulatory requirements and building design relationships. The reliance on transformer models and an IFC knowledge graph hints at underlying challenges which are relevant to all efforts to implement ML for ACC, that is the potential for overfitting to specific regulatory contexts and the difficulty in generalizing across the varied landscape of building codes and design practices. Nevertheless, integrating ML into the regulations – design alignment process represents a significant advantage over traditional hard-coded rules, as it allows for much more flexibility.

In line with these advancements, Chen et al. (2024) proposed a compliance-checking framework that integrated large language models (LLMs) with deep learning models and ontology-based domain knowledge. Their approach sought to minimize the need for extensive manual feature engineering. The framework utilized deep learning models to classify regulatory texts into relevant categories, thereby enhancing the accuracy of information extraction by pre-processing the input for the LLMs. Still, challenges in handling nested or conditional clauses within regulatory texts persisted.

Li et al. (2024a) further enhanced the reasoning capability of intelligent compliance-checking systems by integrating LLMs with knowledge graphs. Their framework evaluated multiple LLMs, including ChatGPT-3.5, ChatGLM-6B, and ERNIE Bot, to determine the most effective model for processing construction schemes. Among these, ChatGPT-3.5 achieved the highest accuracy, demonstrating superior performance in both quantitative and qualitative compliance checks, with an overall accuracy of 72%. The study also highlighted several limitations that required further attention. The dataset utilized in the experiments was relatively small and did not encompass all types of construction schemes, suggesting that further evaluation across complex and diverse scenarios is needed. Additionally, the current knowledge graph of construction standards was constructed manually, which was labor-intensive and time-consuming.

Another well-known challenge when dealing with ML applications, in any domain, is the need for large, labeled data sets. To overcome the challenge of data scarcity in applying ML for ACC, Bloch et al.(Bloch et al. 2023, 2024) proposed using Graph Neural Networks (GNNs) to assess code compliance while relying on a synthetic data set for training. The authors illustrate a proof of concept for implementing a GNN model that was trained on a synthetic data set for code compliance checking. Specifically, they demonstrated a GNN based workflow for checking accessibility requirements in single-family houses. This research marks a significant departure from traditional approaches to ACC, showcasing a potential ML based workflow that elevates the need for rule interpretation. Despite the promising outcomes, such alternative methods have significant limitations. For example, the dynamic nature of regulations might necessitate retraining the model to accommodate changes. We can assume that the complexity of updating rule sets vs. the complexity of retraining ML models will highly depend on the regulations at hand. Overall, it remains unclear which approach poses greater difficulty.

To sum up, although the publications in this group present a full checking procedure, most are predominantly focused on regulatory text analysis. Therefore, we observe a strong link between the work in group 1 and in group 3, especially in the significant role of NLP techniques. The main challenge addressed in the publications in group 3 is bridging the gap between regulatory requirements and digital building model representations. Building on insights from prior research, the proposed integration of advanced technologies like ML, NLP, LLM, and GNN into compliance checking frameworks marks a significant step toward realizing highly automated systems. However, the effectiveness of these methods across various regulations and different scenarios (such as different building types) remains unclear.

4. OPPORTUNITIES AND CHALLENGES IN ML IMPLEMENTATION FOR ACC

Research efforts in ACC are mostly focused on interpretation of regulations and processing of design information. These are interconnected and complementary efforts as the aim usually remains true to the initial process definition by Eastman et al. (2009). Hence most of the work follows the four stages: rule interpretation, preprocessing of design, implementation, and report. While a portion of the reviewed publications illustrate this entire procedure, most of the existing work is predominantly focused on the translation of regulatory documents into computer readable representations. Interpreting regulations expressed in natural text to extract and define relevant rules requires significant domain knowledge and a deep understanding of the regulations. Despite the recent advances, human expertise is indispensable for resolving ambiguities and inconsistencies often encountered in regulatory documents.

We can see a shift towards exploring the potential of ML for processing design data, and even transforming the entire checking process to a ML based process. Currently, preprocessing design data is a significant manual effort, required to resolve inconsistencies, misrepresentations, and errors, as well as supplementing rich and specific information needed for checking. Furthermore, alignment between the regulatory concepts and the concepts represented in the design is yet another task that requires human comprehension and manual engineering work. In these settings, the automated code compliance checking process becomes semi-automated at best, as the manual efforts simply shift from the actual checking process to rule interpretation and fulfilling design information requirements. Accompanied by the restricted range of regulations that currently can be checked automatically (mostly prescriptive and simple requirements), the significance of ACC and its contribution to the industry has become limited. The need for more advanced and sophisticated approaches is evident.

Indeed, we can see a variety of approaches and methods that have been investigated in the reviewed publications. Table 2 presents the techniques that have been implemented in more than four publications in the set of publications that we reviewed. While this analysis provides an overview of current methods, it also reveals important areas for further research. This highlights a significant gap in understanding the comparative efficiency of these techniques. By applying various techniques for checking the same set of regulations, researchers can directly compare performance metrics like accuracy, precision, recall, and processing time. This will provide a deeper understanding of each method's strengths and limitations, potentially leading to the development of more effective hybrid solutions. Such comparative work is currently unavailable, which forms an existing knowledge gap and a valuable direction for future research. In addition, while some ML methods, such as BiLSTM, and Word2Vec have been extensively studied (Table 2), promising approaches like GNNs (Bloch et al. 2023, 2024) have received limited attention in the ACC context. Similarly, emerging trends like large language models (LLMs) still possess strong capabilities that remain largely unexplored in the current literature (Chen et al. 2024; Fuchs et al. 2022; Li et al. 2024a; Zhang 2023).

Table 2: Most utilized techniques.

#	Techniques	References
1	NLP (Natural Language Processing)	(Chen et al. 2024; Fuchs et al. 2022, 2023; Guo et al. 2021; Kruiper et al. 2021, 2024; Li et al. 2020; Li and Cai 2015; Peng and Liu 2023; Purushotham et al. 2024; Salama and El-Gohary 2013, 2011a; b, 2016; Schönfelder and König 2021; Uhm et al. 2015; Wang and El-Gohary 2022, 2023a; b; Xu et al. 2019, 2020; Xu and Cai 2021; Xue et al. 2024; Xue and Zhang 2020a; b, 2021, 2022; Zhang 2023; Zhang and El-Gohary 2012a; b, 2013, 2016a, 2015a; b, 2016b, 2017, 2019a; b, 2020a; b, 2021, 2022a; b, 2018; Zheng et al. 2022; Zhou and El-Gohary 2014a; b, 2015, 2016a; b, 2017, 2021; Zhou et al. 2022a; b)
2	Ontology-Based Methods	(Guo et al. 2021; Kruiper et al. 2024; Li and Cai 2015; Peng and Liu 2023; Uhm et al. 2015; Xu and Cai 2021; Xue and Zhang 2022; Zhang and El-Gohary 2012a; b, 2013, 2015b, 2016b, 2017; Zheng et al. 2022; Zhou and El-Gohary 2014b, 2015, 2017, 2021; Zhou et al. 2022a; b)
3	BiLSTM (Bidirectional Long Short-Term Memory)	(Chen et al. 2024; Kruiper et al. 2021; Li et al. 2020, 2024a; Wang and El-Gohary 2023a; b; Xue and Zhang 2021; Zhang and El-Gohary 2019b, 2020a; b, 2021, 2022a; b)
4	Unsupervised ML (Word2Vec)	(Guo et al. 2021; Li et al. 2020; Li and Cai 2015; Peng and Liu 2023; Wang and El-Gohary 2022, 2023a; Zhang and El-Gohary 2019b, 2020c; Zheng et al. 2022; Zhou and El-Gohary 2014b, 2021)
5	SVM (Support Vector Machine)	(Koo and Shin 2018; Salama and El-Gohary 2016; Wu et al. 2022; Zhang and El-Gohary 2016a, 2020c; Zhou and El-Gohary 2014a, 2016a; b)
6	Transformer models (e.g. BERT)	(Chen et al. 2024; Fuchs et al. 2022, 2023; Kruiper et al. 2021; Li et al. 2024a; Schönfelder and König 2021; Wang and El-Gohary 2024; Xue et al. 2024; Xue and Zhang 2021; Zhang and El-Gohary 2023; Zhou et al. 2022b)
7	NB (Naive Bayes)	(Salama and El-Gohary 2016; Zhang and El-Gohary 2016a; Zhou and El-Gohary 2014a, 2016a; b)
8	MLP (Multi-Layer Perceptron)	(Wang and El-Gohary 2022, 2023b; Zhang and El-Gohary 2019b, 2020c)
9	Unsupervised ML (GloVe)	(Wang and El-Gohary 2023a; b; Zhang and El-Gohary 2021, 2022b)
10	NN (Nearest Neighbors)	(Zhang and El-Gohary 2016a; Zhou and El-Gohary 2014a, 2016a; b)

While there is a noticeable shift towards more sophisticated methods in ACC, our literature review revealed three persistent challenges that were pointed out by many researchers. Table 3 presents the identified challenges and the research papers that discuss them. The challenge that has been mentioned in 59 out of 71 reviewed publications is the scalability of the proposed approaches. Many researchers have emphasized the importance of testing the proposed methods on different regulations and standards to ensure their adaptability and broad applicability. The reviewed publications are usually focused on specific test cases, and while they present valid solutions, it is not clear how the same methods will perform in different scenarios. This scalability issue is crucial because building codes and regulations can vary significantly across jurisdictions, requiring ACC systems to be flexible and capable of accommodating diverse regulatory frameworks.

Table 3: Addressed Challenges.

Challenges	Scalability	Data needs	Benchmark
Machine readable regulations	(Fuchs et al. 2022, 2023; Kruiper et al. 2021, 2024; Li et al. 2020; Purushotham et al. 2024; Salama and El-Gohary 2013, 2016; Schönfelder and König 2021; Uhm et al. 2015; Wang and El-Gohary 2022, 2023a; b; Xu et al. 2019; Xu and Cai 2021; Xue et al. 2024; Xue and Zhang 2020b, 2021, 2022; Zhang and El-Gohary 2012a; b, 2015b, 2016b, 2019b, 2020a; b, 2021, 2022a; b, 2018; Zhou and El-Gohary 2014a; b, 2015, 2016a; b, 2017; Zhou et al. 2022a; b)	(Fuchs et al. 2022, 2023; Kruiper et al. 2021, 2024; Li et al. 2020; Salama and El-Gohary 2016; Schönfelder and König 2021; Wang and El-Gohary 2022, 2023a; b; Xu et al. 2019, 2020; Xu and Cai 2021; Xue et al. 2024; Xue and Zhang 2021, 2022; Zhang and El-Gohary 2019a; b, 2020a; b, 2021, 2022a; b; Zhou and El-Gohary 2014a; b, 2016a; b; Zhou et al. 2022b)	(Kruiper et al. 2024; Salama and El-Gohary 2013; Schönfelder and König 2021; Wang and El-Gohary 2022, 2023b; Xue and Zhang 2020a; b; Zhang and El-Gohary 2020b, 2021, 2022a; b; Zhou and El-Gohary 2014a, 2016a; b, 2017; Zhou et al. 2022b)
	38	28	16
Machine readable design	(Bloch and Sacks 2018; Dinis et al. 2022; Fei et al. 2022; Koo and Shin 2018; Wu et al. 2022; Zhang and El-Gohary 2016a, 2015a, 2016c; Zheng et al. 2022)	(Bloch and Sacks 2018; Dinis et al. 2022; Fei et al. 2022; Koo and Shin 2018; Luo et al. 2022; Wu et al. 2022; Zheng et al. 2022)	(Bloch and Sacks 2018; Dinis et al. 2022; Wu et al. 2022; Zheng et al. 2022)
	9	7	4
Checking mechanism	(Bloch et al. 2023, 2024; Chen et al. 2024; Guo et al. 2021; Li et al. 2024a; Peng and Liu 2023; Wang and El-Gohary 2024; Zhang and El-Gohary 2013, 2017, 2020c, 2023; Zhou and El-Gohary 2021)	(Bloch et al. 2023, 2024; Guo et al. 2021; Li et al. 2024a; Zhang and El-Gohary 2020c, 2023; Zhou and El-Gohary 2021)	(Bloch et al. 2023; Chen et al. 2024; Li et al. 2024a; Li and Cai 2015; Wang and El-Gohary 2024; Zhang and El-Gohary 2017, 2020c, 2023; Zhou and El-Gohary 2021)
	12	7	9

Furthermore, when machine learning models are trained, they are typically designed for a specific target, such as a particular regulatory requirement. However, their performance when accommodating a broader range of targets, such as different regulatory requirements or varying building codes, remains unclear. Different requirements may necessitate entirely different training sets to capture the unique characteristics of each regulation. This variability poses a significant challenge for the scalability and generalizability of ML-based ACC systems and defines an important direction for future research. This also introduces the second challenge, which is the need for good quality data sets for training. The lack of training data has been mentioned in 42 publications out of the 71 reviewed publications (see Table 3). The diversity of building codes and regulations means that ML models must be trained on a wide variety of datasets that accurately reflect this variability. However, compiling such datasets is not straightforward; it requires extensive data collection, labeling, normalization, and validation efforts to ensure that the training data is comprehensive and representative.

Finaly, 29 out of 71 reviewed publications mention the difficulty that arises due to the absence of benchmarks or baselines in the ACC field, which makes it challenging to evaluate and compare the developed models consistently. This absence also complicates efforts to identify the strengths and weaknesses of each method, making it difficult to understand which techniques are most suitable for specific types of regulations or design complexities.

Moreover, without a common baseline for evaluation, researchers cannot effectively measure progress in the field, and it is much harder to progress with adoption of these methods in the industry.

Surprisingly, the reliability of the results was not discussed in the reviewed publications. Reliability is always an issue when dealing with ML, especially in the context of ACC, the non-deterministic results present a significant challenge. Although the reviewed work demonstrated high accuracy in most cases, ML introduces a level of uncertainty to the results. This uncertainty can pose challenges in critical decision-making processes, such as building permitting where code compliance checking is a significant factor. Currently, there are no methods for quantifying and managing these uncertainties and no research direction has been identified for proposing uncertainty aware decision-making frameworks tailored for ACC applications. These could be for example hybrid approaches that combine the strengths of both rule-based systems and ML models to leverage the benefits of both but at the same time mitigate the impact of the non-deterministic results provided by ML techniques. Such hybrid approaches will seek to reduce the needed manual effort in the checking process but expand the scope of regulations that can be checked automatically.

5. CONCLUSIONS

Results of the literature review shed light on the current landscape and the future prospects of automated code checking research. The literature demonstrates the widespread application of ML-based approaches to enhance ACC processes. Notably, there has been a significant focus on transforming regulatory documents into machine-readable representations, with over 60% of reviewed publications discussing the use of ML for interpreting regulatory requirements. In this field, ML and NLP techniques have played a pivotal role in preprocessing regulatory documents, extracting key terms, and transforming information into logical statements. For dealing with design information, efforts have been made to enhance the semantic enrichment of BIM models. In this field, various ML algorithms have been explored from the classic supervised ML models to the more advanced graph-based learning techniques.

The conducted review allows us to answer the posed research questions. Addressing RQ 1, we see that ML-based approaches have been primarily focused on the interpretation of regulations. While other parts of the ACC process have been addressed as well, they have not been thoroughly examined. In addition, while a variety of techniques have been investigated, some remain underexplored. For example, we found only three papers that utilized GPT(Chen et al. 2024; Li et al. 2024a; Zhang 2023), a powerful large language model that has demonstrated remarkable capabilities across various domains. The potential of GPTand similar advanced language models in interpreting and applying building codes remains largely unexplored in the ACC field. These observations highlight a significant opportunity for further research and development.

As for the second research question (RQ 2), ML offers significant opportunities for advancing ACC by enabling the automation of complex regulatory checks, even in the face of inherent ambiguities in natural language and the complexity of design. However, integration of ML solutions with ACC presents several challenges. As shown in Table 3, most of the existing research efforts point to three main challenges which are scalability, lack of data sets for training, and lack of benchmarks for evaluation of the models. Surprisingly, the fact that ML models are not deterministic, and the implication of that on the ACC procedures, was rarely mentioned in the reviewed publications. This may indicate two things: either researchers strongly believe in the ability to achieve very accurate results using ML, or that the practical implementation and integration in the industry of the suggested developments has not been investigated yet. This leads to the last question posed in this work (RQ 3), which aims to identify the promising future research directions. From this study, several directions for further research are evident:

1. Exploration and comprehensive evaluation of additional techniques:

Several ML techniques have been explored for specific tasks of automated compliance checking (Table 2). However, some promising technologies such as GNNs, LLMs, transfer learning and ensemble models have not been sufficiently investigated in this context. To fully understand the capabilities of different approaches for ACC, it is essential to test these methods across various regulations and diverse design contexts. Further research is needed to consider and evaluate additional techniques and algorithms. A thorough evaluation and comparison between the performance of different methods for ACC will provide insights into the strengths and limitations of each approach, allowing more informed decisions about where and how each technique should be deployed. In addition, further investigation into how to breakdown the regulatory documents into specific tasks and how to match each task with the most suitable approach for solution is needed as well.

2. Testing across different scenarios:

Further work is needed for enhancing the scalability of ML models within the ACC domain. This requires testing the performance of each investigated method in different scenarios (different regulations, different building types, different design complexity, etc.). Here, scarcity of labeled data sets, both containing design information and regulatory information, is a notable challenge. Further efforts for synthetic data generation may be beneficial for advancing ML-based ACC solutions. Another direction is collecting and managing data sets from the industry. By fostering a culture of open collaboration and data sharing among researchers, practitioners, regulatory bodies, and industry stakeholders, we can create a more robust foundation for ACC development. The underlying questions in this context are what kind of data is needed and how should it be labeled? How should the data be represented in terms of appropriate formats for ML applications?

3. Developing standardized benchmarks:

Currently, the lack of consistent benchmarks makes it challenging to objectively evaluate and compare different ACC approaches. This includes not only ML models, but also other methods that have been considered. Without standardized metrics and test cases, it is difficult to determine the relative effectiveness of various methods, particularly when applied to different regulatory contexts and design scenarios. Benchmarks could help bridge the gap between research and practice by ensuring that ACC solutions are rigorously tested and validated before deployment in real-world applications. In this domain, human experts have traditionally performed the design review tasks, while using their own knowledge, experience, and the ability to comprehend and interpret both regulations and the design. Currently there are no measures, or any studies to capture the rate of mistakes that these experts make, and therefore it is difficult to establish a baseline for assessing the performance of any automated tools.

4. Integration of Hybrid Approaches:

Each ACC approach has specific capabilities and inherent limitations. Therefore, integrating different techniques into a hybrid approach could potentially lead to a more automated and efficient ACC process. Such approaches can be designed to leverage the strengths and mitigate the limitations of each technique, aiming to provide more flexibility, reduce the manual effort required in the checking process and extend the scope of regulations that can be automatically checked. Integrating diverse methods into a unified framework holds the potential to significantly enhance the automation levels within the ACC process while maintaining satisfactory checking accuracy.

To sum up, this paper presents a comprehensive literature review on the use of ML for ACC. Through this review we have explored the benefits and strength of various ML techniques utilized for ACC. Our analysis revealed the main limitations and persisting challenges in this domain and highlighted the existing knowledge gaps and directions for future research.

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