TDK-thesis

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Integration of Artificial Intelligence in Construction Industry

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Chapter 1

Introduction

The integration of Artificial Intelligence (AI) in the construction industry is a transformative shift that utilizes cutting-edge technologies such as Natural Language Processing (NLP) and stable diffusion algorithms to revolutionize traditional construction methods [1]. NLP enables seamless communication between human stakeholders and AI systems, facilitating efficient data processing and decision-making [1]. This allows for more efficient and effective collaboration between AI-driven systems and human expertise, leading to faster project completion, cost-effectiveness, and improved overall quality [1].

One key application of AI in construction is through AI-powered image recognition algorithms, which play a pivotal role in ensuring accurate and swift analysis of vast amounts of visual data [1]. These algorithms enhance safety protocols by detecting potential hazards in real-time and contribute to the creation of precise floor plans and 3D models [1]. Additionally, stable diffusion techniques in AI optimize resource allocation and project timelines, mitigating bottlenecks and ensuring a steady workflow [1].

The use of AI in construction projects has surged in recent years and is believed to represent a significant potential for increasing productivity and efficiency in the industry [2]. The integration of AI technologies in the construction industry streamlines processes and delivers projects with unprecedented efficiency and accuracy [2]. This paradigm shift in the construction industry embraces AI technologies to streamline processes and deliver projects with unprecedented efficiency and accuracy [2].

The application of AI in the construction industry is also seen as a means to achieve sustainable development [3]. AI has emerged as a promising technology for tackling challenges in the oil and gas industry and has the potential to contribute to sustainable development in this sector [3]. Furthermore, the integration of AI in the construction industry can help increase automation and provide better competitive advantages [4].

In conclusion, the integration of AI in the construction industry represents a transformative shift that utilizes cutting-edge technologies such as NLP and stable diffusion algorithms to revolutionize traditional construction methods. This integration fosters a dynamic construction environment where AI-driven systems collaborate with human expertise, leading to faster project completion, cost-effectiveness, and improved overall quality. The use of AI in construction projects has surged in recent years and is believed to represent a significant potential for increasing productivity and efficiency in the industry. Additionally, the application of AI in the construction industry has the potential to contribute to sustainable development and provide better competitive advantages.

Chapter 2

A brief history of AI

The history of artificial intelligence (AI) can be traced back to ancient times when the concept of intelligent artificial beings created by master craftsmen was believed [5]. However, the roots of modern AI can be attributed to philosophers who described human thinking as symbol manipulation [6]. Formal AI research began in 1956 at Dartmouth College, leading to significant funding and discussions about electronic brains [7]. However, AI faced challenges and experienced periods of reduced funding known as "AI winters" [7]. In the 21st century, AI gained momentum due to advances in machine learning, powerful hardware, and big data [5].

2.1 Early Concepts and Philosophical Foundations (Ancient Times - 1940s)

The history of AI can be traced back to ancient times when the concept of intelligent artificial beings was believed [8]. Philosophers explored the idea of human thinking as symbol manipulation, laying the groundwork for the development of AI. In the 1940s, the introduction of programmable computers sparked discussions about electronic brains and the potential for creating artificial intelligence [8].

These early concepts and philosophical foundations set the stage for further advancements in AI research. The work of Alan, particularly his paper "Computing Machinery and Intelligence," played a significant role in shaping the understanding of AI and its potential [8]. Additionally, the logical calculus of ideas immanent in nervous activity proposed by provided insights into the computational aspects of AI [9].

The exploration of AI also intersected with other disciplines. discussed the social sciences' insights into explanation in artificial intelligence, highlighting how social explanations account for attributing deliberative behavior to groups without referring to intention [10]. The relationship between technology and mathematics was also examined, emphasizing the importance of sound mathematical foundations for advances in AI [11].

During this period, the field of AI was still in its early stages, and there were debates and discussions surrounding its philosophical and theoretical underpinnings. The development of neuromorphic spiking neural networks and their hardware implementations showcased the efforts to mimic the brain's functionality in AI systems [12].

2.2 Formalization and Birth of AI (1952-1956)

In the 1950s, discussions about artificial brains and the potential for creating intelligent machines led to the formalization of AI research, establishing it as an academic discipline McCulloch & Pitts [9]. This period witnessed significant developments that laid the foundation for the birth of AI as a distinct field of study.

One notable event during this time was the Dartmouth Workshop held in 1956 [13]. The workshop brought together leading researchers in the field, including John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon, among others. The Dartmouth Workshop is widely regarded as a pivotal moment in the history of AI, as it marked the birth of the field as an organized and recognized discipline.

During the Dartmouth Workshop, the participants discussed various aspects of AI, including problem-solving, learning, and language processing. One of the key achievements of the workshop was the development of the "Logic Theorist" by Allen Newell and Herbert A. Simon [13]. The Logic Theorist was a computer program designed to prove mathematical theorems using symbolic logic. Its success in proving a range of theorems demonstrated the potential of AI and showcased the power of symbolic manipulation in problem-solving.

Furthermore, it was during the Dartmouth Workshop that the term "Artificial Intelligence" was coined [13]. John McCarthy, one of the workshop organizers, proposed the term to describe the field of study focused on creating intelligent machines. The term "Artificial Intelligence" quickly gained popularity and became the standard label for the field.

The formalization of AI research during this period laid the groundwork for subsequent advancements in the field. It provided a framework for researchers to explore and develop new algorithms, models, and techniques for creating intelligent systems. The Dartmouth Workshop served as a catalyst for further research and collaboration, leading to the establishment of AI as a distinct and rapidly evolving discipline.

2.3 Golden Age of AI Research (1956-1974)

Following the Dartmouth Workshop in 1956, AI research entered a period of optimism and growth, often referred to as the "Golden Age" of AI. During this time, significant advancements were made in various key approaches, including reasoning as search, natural language processing, micro-worlds, and advancements in automata and robotics. The field received substantial funding from organizations like the Defense Advanced Research Projects Agency (DARPA), which supported major AI research centers and fostered a vibrant research culture [8] [14].

One of the key approaches that emerged during this period was reasoning as search. Researchers such as Allen Newell and Herbert A. Simon developed the General Problem Solver (GPS), a program that used a problem-solving approach based on search algorithms. This approach laid the foundation for later developments in areas such as expert systems and knowledge representation [15].

Natural language processing also saw significant progress during the Golden Age of AI. Researchers like Joseph Weizenbaum developed early natural language processing systems, such as ELIZA (2.1), which simulated conversation by using pattern matching techniques [16]. These early systems paved the way for advancements in machine translation, information retrieval, and dialogue systems.

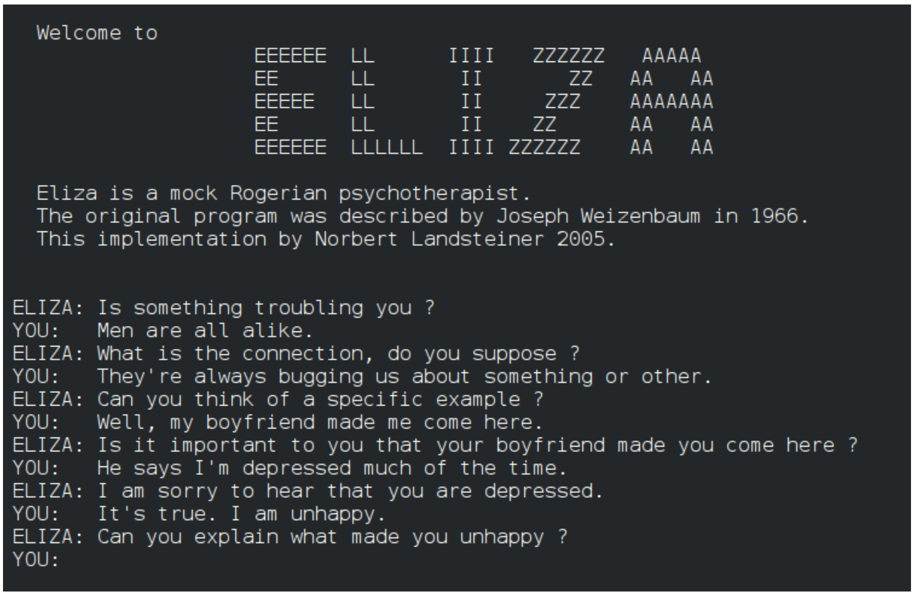

Figure 2.1: Conversation with ELIZA

Micro-worlds, or simplified simulated environments, were another important area of research during this period. Researchers like Marvin Minsky developed micro-worlds such as the Blocks World, which allowed for the exploration of problem-solving and reasoning in a controlled environment [17]. These micro-worlds provided valuable insights into the capabilities and limitations of AI systems.

Advancements in automata and robotics also played a significant role during the Golden Age of AI. Researchers like John McCarthy and the Shakey (2.2) the Robot team at Stanford University developed Shakey, an autonomous robot capable of navigating its environment and performing tasks [18]. This work laid the foundation for future developments in robotics and embodied AI.

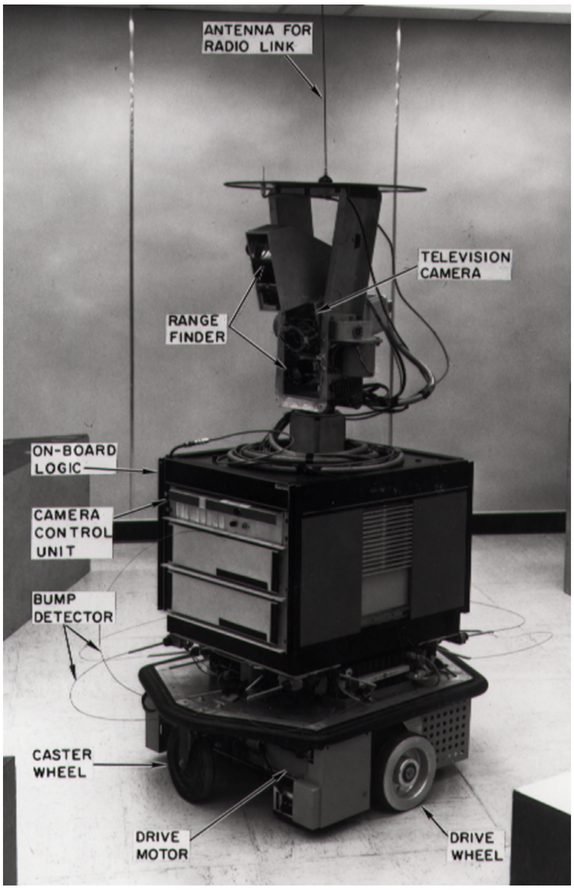

Figure 2.2: SRI's Shakey, the first mobile robot that could make decisions about how to move in its surroundings [19]

The substantial funding provided by DARPA during this period supported major AI research centers, including the Stanford Artificial Intelligence Laboratory and the MIT Artificial Intelligence Laboratory. These centers became hubs of innovation and collaboration, attracting top researchers and fostering a vibrant research culture [20].

The Golden Age of AI Research witnessed remarkable progress and laid the groundwork for future advancements in the field. The key approaches and developments during this period set the stage for the continued growth and evolution of AI as a discipline [20].

2.4 The First AI Winter (1974-1980)

Challenges emerged, leading to financial setbacks during the period known as the First AI Winter (1974-1980). Limited progress, critiques, funding cuts, and the publication of "Perceptrons: An Introduction to Computational Geometry" in 1969 impacted the field Ligęza [6]. The book, authored by Marvin Minsky and Seymour Papert, highlighted the limitations of perceptrons, a type of artificial neural network, and raised doubts about the feasibility of AI research at the time.

The publication of "Perceptrons" had a profound impact on the field, contributing to a period of skepticism and decreased funding for AI projects. The perception of limited progress and the AI effect, which discounts the achievements of AI systems once they are successfully implemented, further contributed to the decline in funding and support for AI research [21].

In response to the challenges faced by AI, researchers began exploring alternative approaches and shifting research directions. Logic programming gained attention as a promising approach during this period [22]. Logic programming focused on using formal logic to represent and reason about knowledge, providing a new perspective for AI research.

Additionally, "anti-logic" approaches, such as connectionism and neural networks, emerged as alternatives to traditional symbolic AI [23]. These approaches aimed to mimic the structure and function of the human brain, emphasizing the importance of parallel processing and distributed representations.

The First AI Winter marked a shift in research directions and a reevaluation of the goals and methods of AI. While the period was characterized by financial setbacks and reduced enthusiasm, it also paved the way for future advancements in AI. The challenges faced during this time led to a deeper understanding of the limitations and complexities of AI systems, setting the stage for subsequent periods of progress and resurgence in the field.

2.5 The AI Boom (1980-1987)

The period from 1980 to 1987 marked an AI boom, characterized by significant advancements and increased interest in the field. Several key developments contributed to the progress of AI during this time.

One notable aspect of the AI boom was the rise of expert systems. Expert systems were computer programs designed to emulate the decision-making capabilities of human experts in specific domains. These systems utilized knowledge bases and inference engines to provide expert-level advice and solutions. The development and deployment of expert systems in various industries, such as medicine and finance, showcased the practical applications of AI [24].

The knowledge revolution also played a significant role during this period. The availability of large amounts of data and the development of techniques for knowledge representation and reasoning fueled advancements in AI. Researchers focused on developing methods to extract, organize, and utilize knowledge effectively, leading to the development of knowledge-based systems [6].

Achievements in chess playing programs also captured public attention and demonstrated the capabilities of AI. In 1985, the chess-playing program Deep Thought defeated a grandmaster for the first time, marking a significant milestone in AI research [24]. This achievement showcased the potential of AI in complex problem-solving and strategic decision-making.

International projects, such as Japan's Fifth Generation Project, contributed to the progress of AI during this period [25]. The Fifth Generation Project aimed to develop advanced computer systems capable of performing intelligent tasks. The project focused on parallel computing, logic programming, and natural language processing, among other areas. Although the project did not achieve all its goals, it stimulated research and collaboration in AI and had a lasting impact on the field.

Advancements in neural networks also played a role in the AI boom. Researchers explored the potential of neural networks for pattern recognition, learning, and decision-making tasks. The development of back propagation, a learning algorithm for training neural networks, in the 1980s further enhanced the capabilities of neural networks [25].

The AI boom of the 1980s witnessed significant progress and increased interest in AI research and applications. The rise of expert systems, the knowledge revolution, achievements in chess playing programs, international projects like Japan's Fifth Generation Project, and advancements in neural networks all contributed to the growth and development of AI during this period.

2.6 Second AI Winter (1987-1993)

The period from 1987 to 1993, known as the Second AI Winter, was characterized by a decline in interest and funding for artificial intelligence (AI) research. Several factors contributed to this downturn, including issues with expert systems, funding cuts, and the emergence of nouvelle AI and embodied reason.

One of the factors that led to the Second AI Winter was the realization of the limitations of expert systems. Expert systems, which were highly specialized AI programs designed to mimic human expertise in specific domains, faced challenges in scaling up and handling uncertainty [25]. The high expectations set for expert systems were not fully met, leading to a decline in confidence and funding for AI projects.

Funding cuts also played a significant role in the Second AI Winter. Government agencies and organizations reduced their financial support for AI research, leading to the closure of AI research centers and a decrease in research activities [25]. The lack of funding hindered progress and innovation in the field, contributing to the decline in AI research during this period.

The emergence of nouvelle AI and embodied reason also impacted the direction of AI research. Nouvelle AI, or "new AI," emphasized the use of sub-symbolic approaches, such as neural networks and connectionism, as alternatives to traditional symbolic AI [26]. These approaches focused on learning from data and pattern recognition, challenging the dominance of symbolic AI.

Embodied reason, which emphasized the importance of physical embodiment and interaction with the environment, gained prominence during this period [27]. Researchers recognized the limitations of purely symbolic approaches and explored the role of embodiment in cognition and intelligence. Robotics and embodied intelligence became areas of focus, challenging the dominance of purely symbolic approaches to AI [28].

Despite the challenges and setbacks faced during the Second AI Winter, the period also laid the groundwork for future advancements in AI. The lessons learned from the limitations of expert systems and the exploration of nouvelle AI and embodied reason paved the way for new research directions and approaches in AI.

2.7 AI (1993-2011)

The period from 1993 to 2011 witnessed significant milestones and advancements in the field of artificial intelligence (AI). These years were marked by notable achievements, the adoption of new approaches, and the integration of AI solutions into various industries.

One of the milestones during this period was the victory of IBM's Deep Blue over world chess champion Garry Kasparov in 1997 Ligęza [6]. Deep Blue's success demonstrated the power of AI in complex strategic decision-making and showcased the advancements in machine learning and search algorithms.

Robotics also made significant strides during this time, with achievements that showcased the capabilities of AI. For instance, the development of autonomous vehicles and humanoid robots demonstrated the progress in perception, motion planning, and control systems [29]. These advancements paved the way for the integration of robots into various domains, including manufacturing, healthcare, and exploration.

Another significant milestone was IBM's Watson winning the Jeopardy! game show in 2011 [30]. Watson's victory demonstrated the advancements in natural language processing, knowledge representation, and probabilistic reasoning. It showcased the ability of AI systems to understand and process human language and access vast amounts of information to provide accurate answers.

During this period, the field of AI embraced intelligent agents as a key approach. Intelligent agents are autonomous entities that perceive their environment and take actions to achieve specific goals. The development of intelligent agents allowed for more sophisticated and interactive AI systems [31].

Probabilistic reasoning also gained prominence during this time. Researchers focused on developing algorithms and models that could handle uncertainty and make decisions based on probabilistic information. Bayesian networks and probabilistic graphical models became important tools for representing and reasoning under uncertainty [32].

The field of AI also embraced rigorous mathematical tools and techniques. Researchers developed formal methods for AI, including logic-based approaches, formal verification, and model checking. These mathematical tools provided a foundation for ensuring the correctness and reliability of AI systems [33].

The integration of AI solutions into various industries was another significant development during this period. AI technologies were applied in areas such as healthcare, finance, transportation, and customer service. AI-powered systems were used for medical diagnosis, fraud detection, autonomous vehicles, and personalized recommendations, among other applications [34].

2.8 2011-Present: Big Data and Advanced Machine Learning

The period from 2011 to the present has been characterized by significant advancements in the field of artificial intelligence (AI), driven by the proliferation of big data and advancements in machine learning. This era has witnessed the emergence of large language models like GPT-3 and GPT-4, which have showcased the capabilities of AI in natural language processing and generation Hey [35].

The importance of big data has been defined by its 5Vs: Volume, Velocity, Variety, Value, and Veracity. The exponential growth in data has driven innovations in data analysis and optimization processes [36]. The ability to collect, store, and process massive amounts of data has opened up new opportunities for AI applications and insights.

Machine learning has played a crucial role in harnessing the power of big data. Advanced machine learning techniques, such as deep learning, have revolutionized AI research and applications. Deep learning models, with their ability to automatically learn hierarchical representations from large-scale data, have achieved remarkable success in various domains, including computer vision, natural language processing, and speech recognition [37].

The integration of big data and advanced machine learning has led to significant advancements in various fields. In healthcare, AI-powered systems have been developed for disease diagnosis, drug discovery, and personalized medicine [38]. In finance, big data analytics and machine learning algorithms have been used for fraud detection, risk assessment, and algorithmic trading [39]. In agriculture, AI and big data have been employed for precision farming, crop yield optimization, and pest management [40].

The era of big data and advanced machine learning has also witnessed advancements in data analytics and optimization techniques. Researchers have developed new algorithms and models to extract insights from complex and high-dimensional data, enabling better decision-making and resource allocation [41]. The integration of big data analytics and AI has also led to the development of intelligent systems that can process and analyze data in real-time, enabling timely and informed decision-making [42].

The impact of big data and advanced machine learning extends beyond technical domains. In education, AI-powered systems have been used for personalized learning, adaptive assessments, and intelligent tutoring [43]. In libraries and information management, big data analytics have been employed for data-driven decision-making, user behavior analysis, and content recommendation [44]. The application of big data and AI has also raised important ethical and privacy concerns, highlighting the need for responsible and transparent practices [45].

The era of big data and advanced machine learning continues to evolve rapidly, with ongoing research and advancements in AI algorithms, data management, and computing infrastructure. As the volume and complexity of data continue to grow, the integration of big data and AI will play a crucial role in unlocking new insights, driving innovation, and addressing complex challenges across various domains.

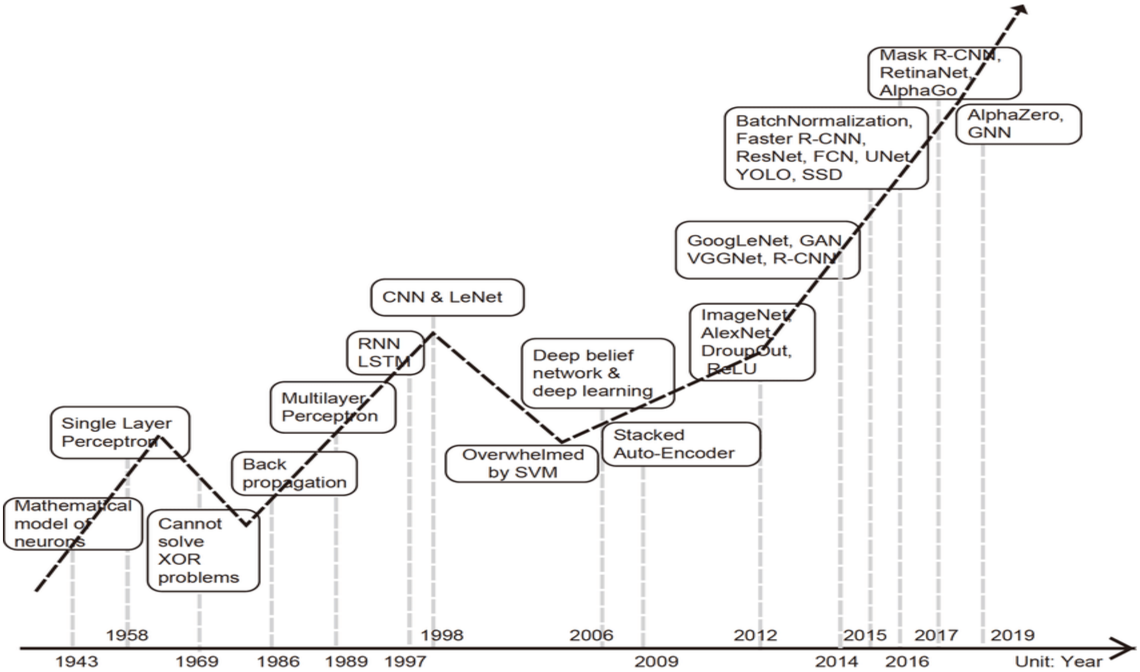

Figure 2.3: AI milestones

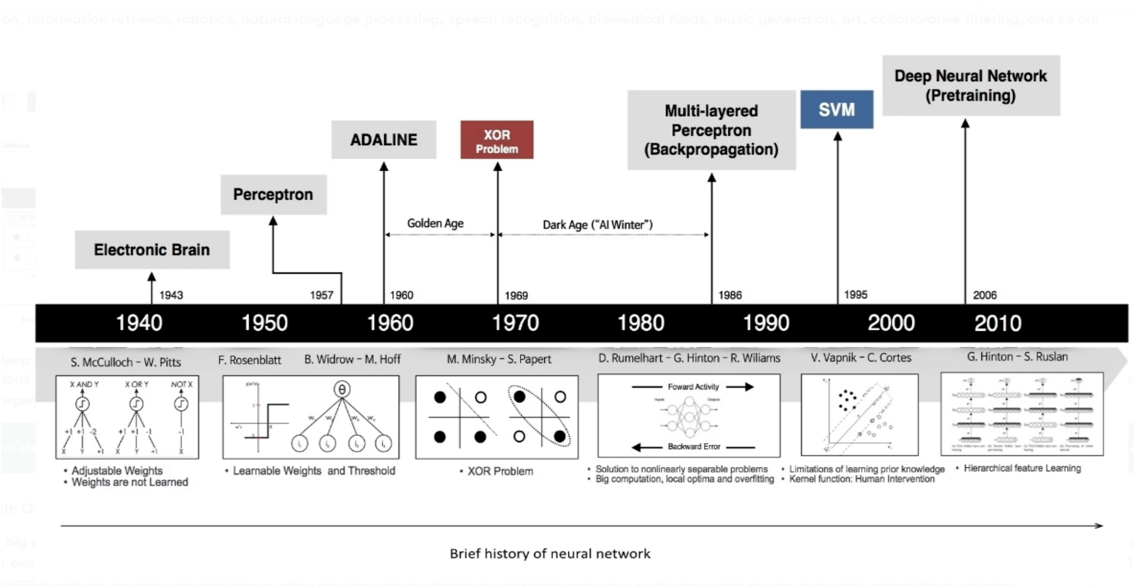

Figure 2.4: Brief history of Neural Networks

Chapter 3

Current appliances of AI in Engineering

Artificial intelligence (AI) has advanced significantly in recent years and has the potential to revolutionize various fields of engineering. AI-powered applications can tackle complex engineering problems that traditional methods cannot handle, making them efficient, fast, accurate, and comprehensive.

Different AI methods such as machine learning, genetic algorithms, fuzzy logic, and neural networks have been evaluated and applied in engineering contexts [46]. AI has been used in various stages of the design process, including inspiration, idea generation, evaluation, optimization, decision-making, and modeling [46].

Recent trends in AI applications in engineering include data-based design methods and explainable AI. It is important to choose the appropriate AI method for each engineering problem to achieve successful results.

3.1 Overall use-cases of AI in Engineering

3.1.1 AI-powered Design and Planning

AI algorithms analyze vast amounts of data to optimize building designs. Machine learning algorithms can assess architectural blueprints, geological surveys, and climate data to create energy-efficient and structurally sound designs [47]. AI also aids in site selection and planning by considering factors like traffic patterns, environmental impact, and accessibility.

3.1.2 Project Management and Scheduling

AI-driven project management tools utilize predictive analytics to create accurate project schedules. These tools analyze historical project data, weather conditions, and other variables to predict potential delays and optimize scheduling [47]. Real-time monitoring through IoT sensors and AI algorithms enables project managers to make data-driven decisions, reducing bottlenecks and improving overall efficiency.

3.1.3 Construction Automation and Robotics

AI-powered robotics and automation systems are being deployed for various construction tasks. Construction robots equipped with AI can perform repetitive tasks such as bricklaying, concrete pouring, and welding with precision and speed. Drones equipped with AI and computer vision are used for aerial surveys, site inspections, and material delivery, enhancing safety and accuracy.

3.1.4 Safety and Risk Management

AI applications, including computer vision and IoT sensors, enhance safety on construction sites. Computer vision algorithms can monitor workers' activities and identify potential hazards, ensuring compliance with safety regulations [47]. Predictive analytics in AI help assess risks associated with different project aspects, enabling proactive risk management and mitigation strategies.

3.1.5 Supply Chain Optimization

AI algorithms optimize the construction supply chain by predicting material requirements, tracking inventory levels, and identifying suppliers offering the best prices and delivery times. Predictive analytics improve procurement processes, reducing costs and delays associated with material shortages [47].

3.1.6 Quality Control and Inspections

AI-driven image recognition and machine learning are utilized for quality control and inspections. These systems can identify defects, deviations from blueprints, and structural issues by analyzing images and sensor data, ensuring that construction projects meet industry standards and regulations [47].

3.2 Specific uses of AI in Construction Industry

3.2.1 Artificial Neural Networks

Artificial neural networks (ANN) have been widely applied in the construction industry for various tasks such as energy efficiency, structural analysis, construction materials, smart city technologies, and more [48].

ANN has been used in heating, ventilation, and air conditioning (HVAC) for analysis and optimization of control systems, as well as predicting non-uniform indoor pollutant concentration.

In structural analysis, ANN has been used for assessing concrete strength and performance, evaluating damage states of steel structures, and assessing various loads.

ANN has also been utilized in construction safety, including the assessment of fire resistance of building materials, safety assessment of mega-projects, evacuation tasks, and forecasting the safety of building structures.

Additionally, ANN has been applied in construction engineering and soil mechanics, as well as in preventing injuries at construction sites [48].

3.2.2 Automated floor plan generation

The authors [49] conducted a literature survey using four main databases, including Web of Science, Google Scholar, Scopus, and CumInCAD, to retrieve research articles for their review paper.

Ramon Elias Weber et al. [49] identified 49 different methods for automated floor plan generation, categorized into three types: bottom-up, top-down, and referential methods.

The authors excluded methods that did not result in a floor plan layout, such as those studying adjacency graphs or building massings.

Referential methods, which involve learning from precedent and using architectural catalogues and previously generated designs, have been of interest in both professional and educational settings. ML algorithms with deep neural networks, such as generative adversarial networks (GANs), as well as mathematical programming methods, have been used in referential design [49] .

3.2.3 Production ready applications of AI in Construction

Below is a table of AI integrated products that are currently offered to solve couple of Construction related problems or provide automation for various processes.

Products		
Name	*Best features*	*Limitations*
ClickUp	• Optimized construction scheduling, • Materials tracking, resource management, • Managing projects with mobile app	• There is a learning curve for using the software • Mobile app is not as developed as PC
OpenSpace.ai	• Creating 360-degree walk-throughs of construction sites, • Creating digital twins on job sites, • Automatically mapping captured images to project plans, • Integrating project data with visual documentation	• Lack of integration with Autodesk products, like Construction Cloud, • Scanning and capturing job site images can be time-consuming

Name	*Best features*	*Limitations*
Procore	• Encompassing tasks such as document control, scheduling, budgeting, and communication, • Enabling seamless collaboration among construction teams, subcontractors, and stakeholders, • Features a dedicated mobile application for enhanced accessibility and convenience.	• Tasks cannot be configured as "recurring.",
Fusion 360 by Autodesk	• Utilizing AI-powered generative design techniques, • Employing advanced parametric modeling techniques, • Incorporating integrated simulation and analysis tools,	• Restrictions on offline capabilities

Name	*Best features*	*Limitations*
Fieldwire	• Facilitating effortless blueprint management and sharing, • Enabling teams to create, assign, and monitor tasks in real time, • Providing in-depth reporting features to offer insights into progress and performance metrics	• Constraints in financial and budget tracking capabilities within the platform
PlanSwift	• Precise and streamlined measurements and calculations extracted directly from digital blueprints and documents, ensuring accuracy and efficiency	• PlanSwift does not provide a cloud-based or server alternative for users, • Potential lag when switching project tabs in the product
DroneDeploy	• Exceptional aerial imaging capabilities for construction sites, • Automated generation of 2D maps and 3D models from drone imagery	• The platform lacks the capability to import 3D models for overlaying designs, • Managing and tracking project deliverables can pose significant challenges within the system

Name	*Best features*	*Limitations*
viAct	• Precision in detecting safety compliance issues and potential hazards, • Early identification of plan deviations using advanced anomaly detection	• The product offers restricted customization features, limiting extensive modifications, • The product lacks Internet of Things (IoT) integration
AI Clearing	• Utilizes sophisticated AI algorithms for automatic identification of safety compliance issues and hazards, • Automated detection of plan discrepancies for prompt corrective action, • Provides robust visual analytics and reporting tools for informed decision-making	• Lack of universal adoption, • Absence of domestic support in the United States

Name	*Best features*	*Limitations*
AVEA Insight	• Optimizes asset performance and risk mitigation with AI-driven predictive maintenance algorithms, • Streamlines IT management with automatic updates and cloud scalability, • Empowers proactive maintenance strategies with advanced pattern recognition	• The product does not offer clash detection features, • It may be better aligned with the requirements of manufacturing industries rather than construction

Table 3.1: AI driven products that are used in Construction Industry

Chapter 4

Use of Natural Language Processing in Construction Industry

4.1 What is NLP?

Natural Language Processing (NLP) is a field of study that focuses on the mathematical and computational modeling of various aspects of language. It involves the development of systems and algorithms that enable computers to understand and process human language. NLP is highly interdisciplinary, drawing concepts from computer science, linguistics, logic, and psychology.

The primary goal of NLP is to enable computers to "understand" and interpret human language, although the definition of "understanding" remains a major challenge in the field [50]. NLP techniques aim to bridge the gap between human language and machine language, allowing computers to analyze, interpret, and generate human language in a meaningful way.

4.2 How NLP can be used in Construction Industry?

NLP has a wide range of applications across different domains, including the construction industry. In construction, NLP can be used to optimize information flow, project management, risk assessment, compliance checking, and supply chain optimization [47]. By leveraging NLP techniques, construction professionals can improve efficiency, accuracy, and decision-making processes.

For example, NLP algorithms can analyze large volumes of construction-related data, such as blueprints, geological surveys, and climate data, to optimize building designs for energy efficiency and structural integrity [47]. NLP can also be used to extract construction quality requirements from textual specifications, automating the information retrieval process and facilitating automated construction inspection [51].

In project management and scheduling, NLP-powered tools can utilize predictive analytics to analyze historical project data, weather conditions, and other variables to create accurate project schedules and predict potential delays [47]. Real-time monitoring through IoT sensors and NLP algorithms enables project managers to make data-driven decisions, reducing bottlenecks and improving overall efficiency.

NLP can also enhance safety and risk management in construction. Computer vision algorithms can monitor workers' activities and identify potential hazards, ensuring compliance with safety regulations [52]. NLP can assist in assessing risks associated with different project aspects, enabling proactive risk management and mitigation strategies [52].

Furthermore, NLP techniques can optimize the construction supply chain by predicting material requirements, tracking inventory levels, and identifying suppliers offering the best prices and delivery times [47]. This improves procurement processes, reduces costs, and minimizes delays associated with material shortages.

In recent years, there has been a significant rise in the popularity and widespread use of Natural Language Processing (NLP) models, with one notable example being the widely recognized "ChatGPT." This model has gained immense attention globally and has been extensively covered in various publications, primarily due to its impressive training data volume. However, it is important to note that while ChatGPT has garnered fascination for its capabilities, its direct applicability to the specialized engineering needs of the construction industry is limited. This limitation arises from the fact that ChatGPT has not been trained on professional datasets that are crucial for generating credible insights specific to the construction field.

4.2.1 Deep Layout Model

Wenming Wu et. al. have proposed a novel data-driven technique for automatically and efficiently generating floor plans for residential buildings with given boundaries [53].

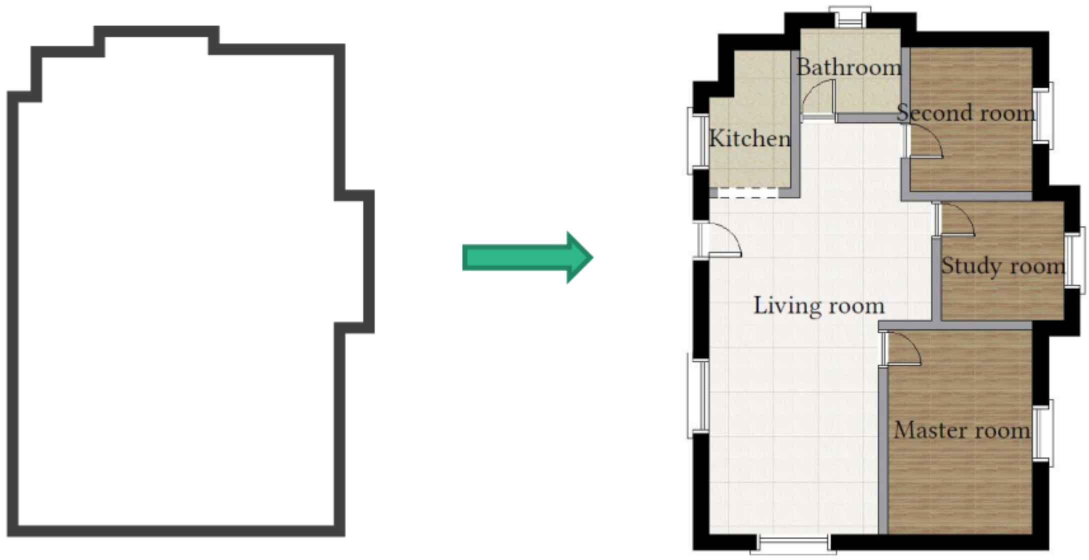

Figure 4.1: General input-output flow

Authors created a two-stage (4.2) approach that imitates the human design process which is locating the rooms first and then walls while adapting to the input building boundary [53].

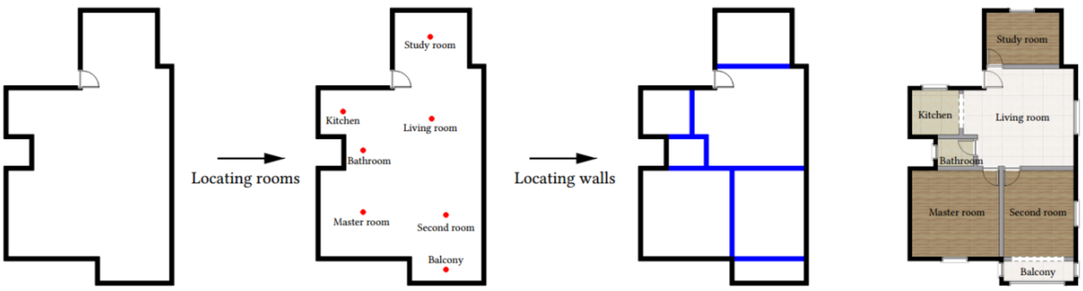

Figure 4.2: Two-stage approach

The proposed network first places living rooms and then iteratively adds other rooms, then, walls are added. In order to train this model they have constructed RPLAN (4.3), a large-scale dataset of floor plans from real residential buildings [53].

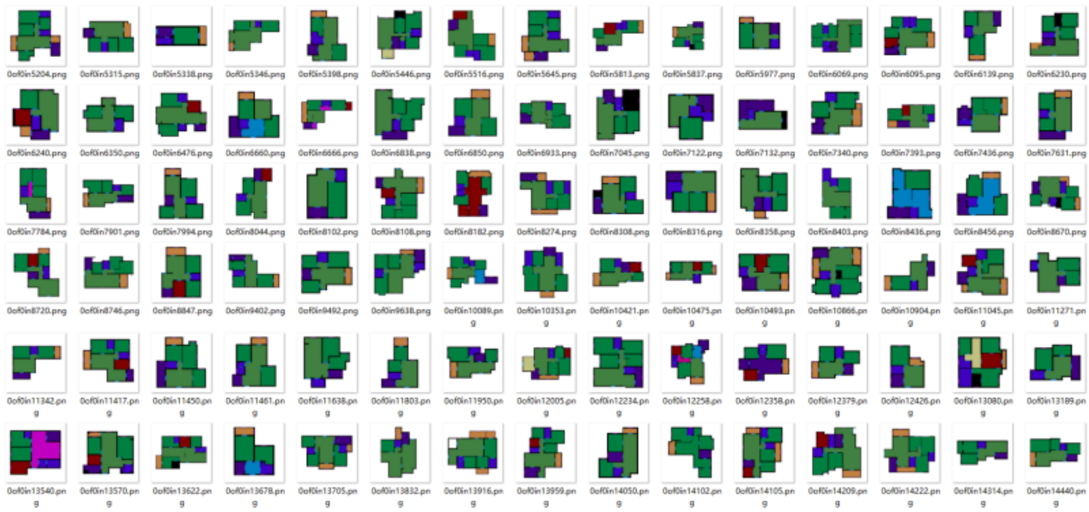

Figure 4.3: RPLAN dataset [53]

Although the current success of this proposed model, it still requires expert-level computer knowledge to be able to harness its power. In addition to this, the model needs a manual input for the room boundary, in order to populate it with rooms. One of the downsides of this is complexity, it is nearly impossible for an ordinary person, without required skills, to operate such a sophisticated piece of technology.

It's also worth mentioning, the training of this complex model, requires 4 to 5 days[53]. And the computer hardware is needed to be high-end, as the main hard work falls onto GPU. Nevertheless, I believe this very model is highly applicable and can be used in a much more complex system, that doesn't require too much time and knowledge to harness its power.

4.2.2 What if?...

Let's imagine a system that integrates an NLP model, the Deep Layout Model (DLM) and specific models for other processes, and an interface to output the generated data. The NLP model should be trained with construction industry specific data, to be able to transform the input accordingly, in order to control inner models.

As the DLM requires specific inputs to generate a floor plan, the trained NLP model should be able to transform natural language to control DLM and other integrated model. What I envision for other models are listed below:

- Produce scripts compatible with software platforms like Revit, Rhino, and Tekla, catering to users with intermediate experience, thereby expediting building creation,

- Provide detailed instructions tailored for experienced users, facilitating the modeling process of their projects
- Offer creative concepts and ideas for building designs in response to requests from inexperienced users,
- Generate estimated cost projections using the Revit API, enhancing project budgeting accuracy,
- Develop Python scripts for Rhino, enabling the generation of algorithmic designs and augmenting the creative potential,
- And encompass additional functionalities vital for addressing diverse construction-related needs

Here I propose the general flow-chart of the main system:

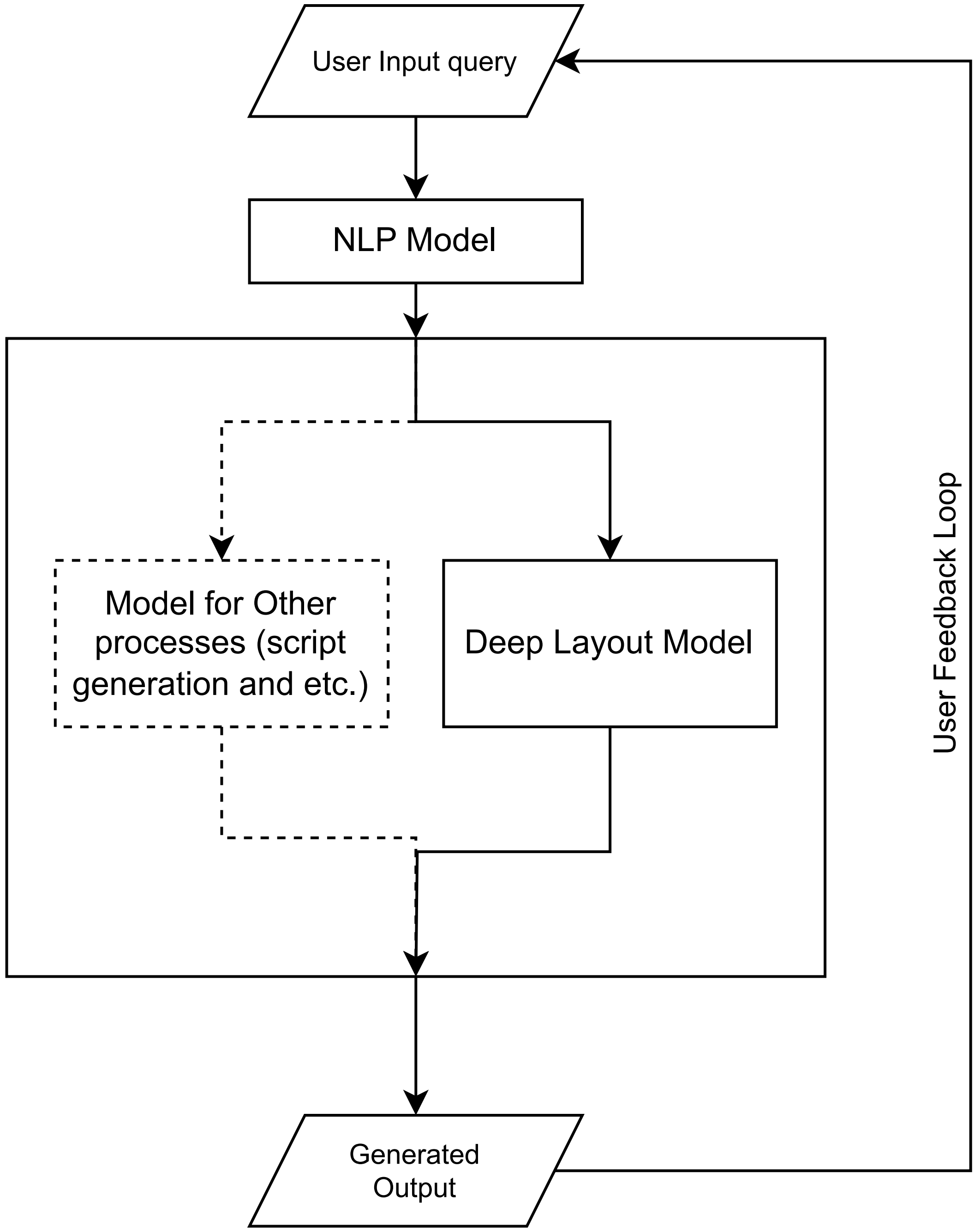

Figure 4.4: General Flowchart of the model

The process is as follows:

1. User interacts with our NLP model
2. NLP model then transforms the query and sends it to inner layout
3. According to the user needs, specific model handles the input
4. Inner layout generates the output
5. The user has the ability to modify and/or add to the query

6. Feedback is initiated and query is sent back to NLP model for further transformations

And here I show much detailed version to express my thought in a better way:

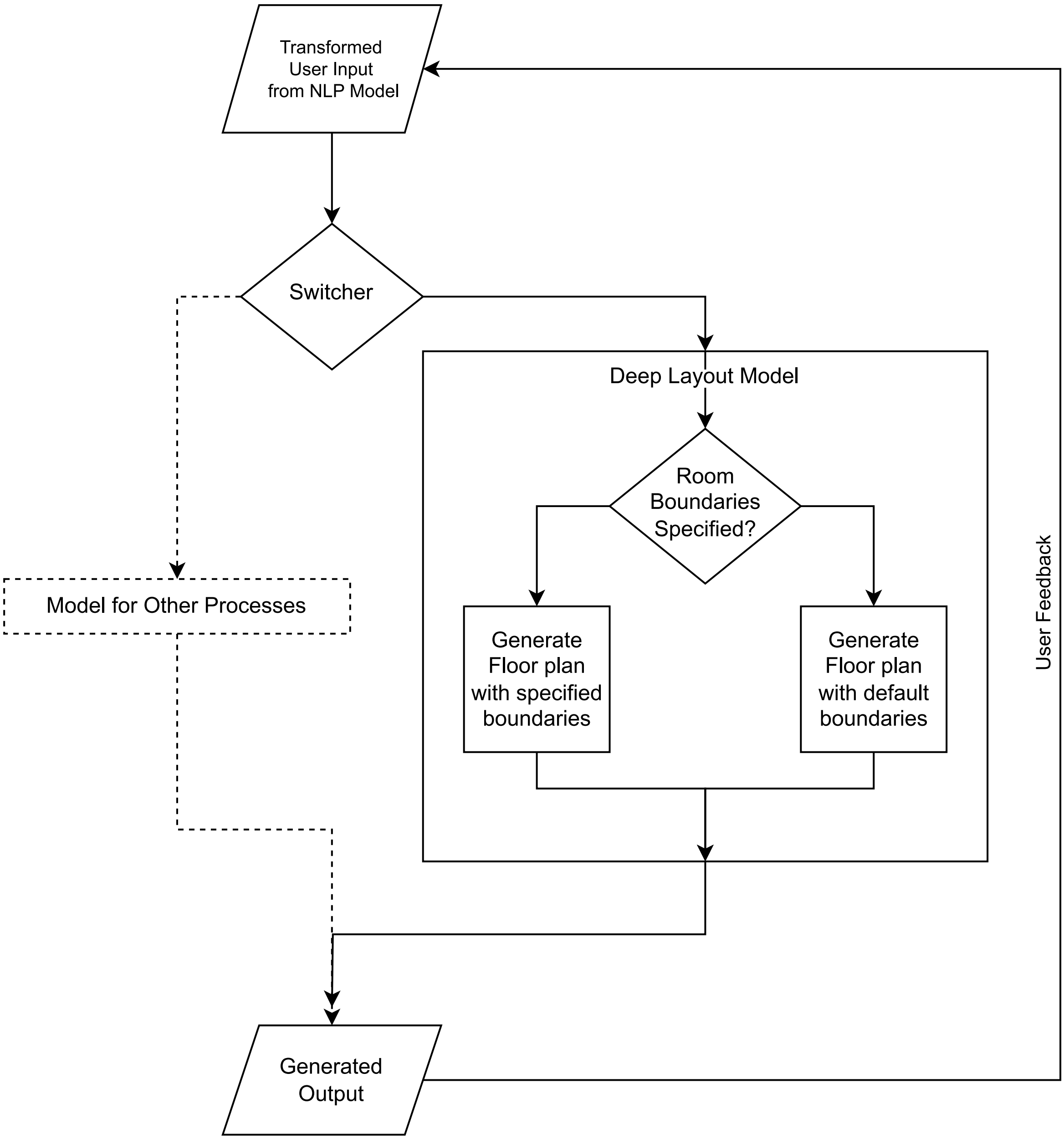

Figure 4.5: A detailed look into the model

As it can be seen from the flow-chart, the system is complex. Below is the process:

1. Transformed user input is sent to the Switcher inside inner layout

2. The Switcher then sends the data to requested models

3. DLM itself has a decision block which checks if user has specified boundaries

   (a) If user has specified boundaries, then the floor plan is generated with given measurements
   (b) If no boundaries have been specified, then the floor plan is generated with default measurements, which will require the NLP model to prompt user in the next cycle to enter measurements

4. After these processes the output is shown to user, waiting for further inputs

Note: The model for other processes is shown in its generalised form for the sake of simplicity

4.2.3 Challenges

The idea seems easy to implement, yet it requires a lot of time to realize. DLM part has its dataset which makes it much easier to work with, but for the NLP part a construction industry related dataset is needed to be created from scratch.

In addition, computers with high-end hardware is needed to carry out the training phase of each model. Here the computing power plays a huge role in the process of maintaining success rate of generated output to be above 80%.

4.2.4 Future expectations

I believe in the viability of this idea as it can be a bridge between ordinary people and sophisticated AI tools, in order to help them realize their ideas into a visible work, by just using their natural language. And if I can prove the applicability of this idea in my future research, I am sure this idea can be scaled up to serve people all around the globe.

My intentions are not to create a system that will replace architects or experts in this field, but to create a tool that will generate alternative solutions for both the users and experts. This system can also be used to connect possible customers to experts, which itself will be a benefit for both parties.

Chapter 5

Conclusion

The concept of creating "artificial intelligence" has always been with us, from the tales to now implemented systems. The history of the current AI shows us that, as the time goes by we are finding much better and efficient options. The continuous advancements in machine learning algorithms have paved the way for AI systems to learn and adapt, making them indispensable tools in our rapidly changing world.

A lot of effort has been put into AI in the past decades, with various tools emerging more victorious and finding their uses in the production of particular industries. AI tools are mainly integrated outside of the construction industry, yet there are various tools that help solve tedious tasks by automating processes. As we move forward, a multidisciplinary approach involving AI, NLP, and domain-specific expertise will be key in shaping the future of problem-solving and decision-making processes.

Natural Language Processing is gaining attraction as the time passes, now it can be used as a tool to learn, and/or to cut the time needed to create projects. In the field of civil engineering, integrating Natural Language Processing with AI models can lead to innovative solutions, streamlining processes and improving the overall project management. As a Civil Engineer I believe we should join this trend to integrate NLP with other existing and proven models to create a much more complex, yet capable system, which in its way will be used to solve problems. By harnessing the power of AI and NLP, we can address complex engineering challenges, optimize designs, and ensure sustainable development.

Bibliography

[1] H. Abbass. “Social integration of artificial intelligence: functions, automation allocation logic and human-autonomy trust”. In: *Cognitive Computation* 11 (2 2019), pp. 159–171. DOI: 10.1007/s12559-018-9619-0.

[2] “Artificial intelligence in construction projects: a systematic scoping review”. In: *Journal of Engineering Project and Production Management* (2022). DOI: 10.32738/jeppm-2022-0021.

[3] A. Waqar et al. “Applications of ai in oil and gas projects towards sustainable development: a systematic literature review”. In: *Artificial Intelligence Review* 56 (11 2023), pp. 12771–12798. DOI: 10.1007/s10462-023-10467-7.

[4] “Research on the application of ai artificial intelligence technology in intelligent buildings”. In: *Academic Journal of Architecture and Geotechnical Engineering* 4 (3 2022). DOI: 10.25236/ajage.2022.040306.

[5] L. David and K. Alan. “Artificial intelligence: foundations of computational agents”. In: *Choice Reviews Online* 48 (04 2010), pp. 48–2130–48–2130. DOI: 10.5860/choice.48-2130.

[6] A. Ligęza. “Artificial intelligence: a modern approach”. In: *Neurocomputing* 9 (2 1995), pp. 215–218. DOI: 10.1016/0925-2312(95)90020-9.

[7] B. Buchanan, J. Eckroth, and R. Smith. “A virtual archive for the history of ai”. In: *Ai Magazine* 34 (2 2013), pp. 86–98. DOI: 10.1609/aimag.v34i2.2455.

[8] A. Turing. “Computing machinery and intelligence”. In: (2007), pp. 23–65. DOI: 10.1007/978-1-4020-6710-5_3.

[9] W. McCulloch and W. Pitts. “A logical calculus of the ideas immanent in nervous activity”. In: *Bulletin of Mathematical Biology* 52 (1-2 1990), pp. 99–115. DOI: 10.1007/bf02459570.

[10] T. Miller. “Explanation in artificial intelligence: insights from the social sciences”. In: *Artificial Intelligence* 267 (2019), pp. 1–38. DOI: 10.1016/j.artint.2018.07.007.

[11] S. Hansson. “Technology and mathematics”. In: *Philosophy and Technology* 33 (1 2019), pp. 117–139. DOI: 10.1007/s13347-019-00348-9.

[12] L. Camuñas-Mesa, B. Linares-Barranco, and T. Serrano-Gotarredona. “Neuromorphic spiking neural networks and their memristor-cmos hardware implementations”. In: *Materials* 12 (17 2019), p. 2745. DOI: 10.3390/ma12172745.

[13] Daniel Shu Wei Ting et al. “Deep Learning in Ophthalmology: The Technical and Clinical Considerations”. In: *Progress in Retinal and Eye Research* (2019). DOI: 10.1016/j.preteyeres.2019.04.003.

[14] Y. Duan, J. Edwards, and Y. Dwivedi. “Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda”. In: *International Journal of Information Management* 48 (2019), pp. 63–71. DOI: 10.1016/j.ijinfomgt.2019.01.021.

[15] L. Catanese, J. Tarsia, and M. Fisher. “Acute ischemic stroke therapy overview”. In: *Circulation Research* 120 (3 2017), pp. 541–558. DOI: 10.1161/circresaha.116.309278.

[16] C. Nelson et al. “Patient perspectives on the use of artificial intelligence for skin cancer screening”. In: *Jama Dermatology* 156 (5 2020), p. 501. DOI: 10.1001/jamadermatol.2019.5014.

[17] L. Maier-Hein et al. “Surgical data science – from concepts toward clinical translation”. In: *Medical Image Analysis* 76 (2022), p. 102306. DOI: 10.1016/j.media.2021.102306.

[18] M. McCradden, T. Sarker, and P. Paprica. “Conditionally positive: a qualitative study of public perceptions about using health data for artificial intelligence research”. In: *BMJ Open* 10 (10 2020), e039798. DOI: 10.1136/bmjopen-2020-039798.

[19] SRI International. *SRI’s Shakey*. License: [CC BY-SA 3.0]. URL: https://commons.wikimedia.org/w/index.php?curid=17294520.

[20] C. Østerlund et al. “Artificial intelligence and the world of work, a co-constitutive relationship”. In: *Journal of the Association for Information Science and Technology* 72 (1 2020), pp. 128–135. DOI: 10.1002/asi.24388.

[21] Ross Gruetzemacher et al. “Forecasting AI Progress: A Research Agenda”. In: *Technological Forecasting and Social Change* (2021). DOI: 10.1016/j.techfore.2021.120909.

[22] Radim Jiroušek. “Expert Systems—Principles and Programming”. In: *Automatica* (1991). DOI: 10.1016/0005-1098(91)90121-h.

[23] Sergey Mileiko et al. “Neural Network Design for Energy-Autonomous Artificial Intelligence Applications Using Temporal Encoding”. In: *Philosophical Transactions of the Royal Society a Mathematical Physical and Engineering Sciences* (2019). DOI: 10.1098/rsta.2019.0166.

[24] Venkat Venkatasubramanian. “The Promise of Artificial Intelligence in Chemical Engineering: Is It Here, Finally?” In: *Aiche Journal* (2018). DOI: 10.1002/aic.16489.

[25] Robert Phelps. “The Fifth Generation: Artificial Intelligence and Japan’s Computer Challenge to the World”. In: *European Journal of Operational Research* (1984). DOI: 10.1016/0377-2217(84)90193-0.

[26] Tom Froese and Tom Ziemke. “Enactive Artificial Intelligence: Investigating the Systemic Organization of Life and Mind”. In: *Artificial Intelligence* (2009). DOI: 10.1016/j.artint.2008.12.001.

[27] Lola Cañamero and Matthew Lewis. “Making New “New AI” Friends: Designing a Social Robot for Diabetic Children From an Embodied AI Perspective”. In: *International Journal of Social Robotics* (2016). DOI: 10.1007/s12369-016-0364-9.

[28] Angelo Cangelosi and Matthew Schlesinger. “From Babies to Robots: The Contribution of Developmental Robotics to Developmental Psychology”. In: *Child Development Perspectives* (2018). DOI: 10.1111/cdep.12282.

[29] Ahmed Hosny et al. “Artificial Intelligence in Radiology”. In: *Nature Reviews Cancer* (2018). DOI: 10.1038/s41568-018-0016-5.

[30] Jianxing He et al. “The Practical Implementation of Artificial Intelligence Technologies in Medicine”. In: *Nature Medicine* (2019). DOI: 10.1038/s41591-018-0307-0.

[31] Nina Schwalbe and Brian Wahl. “Artificial Intelligence and the Future of Global Health”. In: *The Lancet* (2020). DOI: 10.1016/s0140-6736(20)30226-9.

[32] Yu-Meng Lei et al. “Artificial Intelligence in Medical Imaging of the Breast”. In: *Frontiers in Oncology* (2021). DOI: 10.3389/fonc.2021.600557.

[33] Francisco López-Jiménez et al. “Artificial Intelligence in Cardiology: Present and Future”. In: *Mayo Clinic Proceedings* (2020). DOI: 10.1016/j.mayocp.2020.01.038.

[34] Jane Scheetz et al. “A Survey of Clinicians on the Use of Artificial Intelligence in Ophthalmology, Dermatology, Radiology and Radiation Oncology”. In: *Scientific Reports* (2021). DOI: 10.1038/s41598-021-84698-5.

[35] Tony Hey. “The Fourth Paradigm – Data-Intensive Scientific Discovery”. In: (2012). DOI: 10.1007/978-3-642-33299-9_1.

[36] Saint John Walker. “Big Data: A Revolution That Will Transform How We Live, Work, and Think”. In: *International Journal of Advertising* (2014). DOI: 10.2501/ija-33-1-181-183.

[37] Yichuan Wang et al. “An Integrated Big Data Analytics-Enabled Transformation Model: Application to Health Care”. In: *Information & Management* (2018). DOI: 10.1016/j.im.2017.04.001.

[38] Gema Bello-Orgaz, Jason J. Jung, and David Camacho. “Social Big Data: Recent Achievements and New Challenges”. In: *Information Fusion* (2016). DOI: 10.1016/j.inffus.2015.08.005.

[39] H. Li et al. “Application and Platform Design of Geospatial Big Data”. In: *The International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences* (2021). DOI: 10.5194/isprs-archives-xliii-b4-2021-293-2021.

[40] Rahat Iqbal et al. “Big Data Analytics: Computational Intelligence Techniques and Application Areas”. In: *Technological Forecasting and Social Change* (2020). DOI: 10.1016/j.techfore.2018.03.024.

[41] Zhicheng Liu and Aoqian Zhang. "Sampling for Big Data Profiling: A Survey". In: *Ieee Access* (2020). DOI: 10.1109/access.2020.2988120.

[42] Chirihane Gherbi et al. "A Systematic Literature Review of Machine Learning Applications in IoT". In: *International Journal of Communication Systems* (2023). DOI: 10.1002/dac.5500.

[43] Yijun Liu, Yulong Ding, and Jiale Wu. "Research on the Influence of Postgraduate's Big Data Capability on Their Innovation Performance". In: (2022). DOI: 10.2991/978-94-6463-034-3_23.

[44] Ben Kei Daniel. "<scp>B</Scp>ig <scp>D</Scp>ata and Analytics in Higher Education: Opportunities and Challenges". In: *British Journal of Educational Technology* (2014). DOI: 10.1111/bjet.12230.

[45] Lei Wang et al. "BigDataBench: A Big Data Benchmark Suite From Internet Services". In: (2014). DOI: 10.1109/hpca.2014.6835958.

[46] D. T. Pham and P. T.N. Pham. "Artificial intelligence in engineering". In: *International Journal of Machine Tools and Manufacture* 39 (6 June 1999), pp. 937–949. ISSN: 0890-6955. DOI: 10.1016/S0890-6955(98)00076-5.

[47] M. Bilal et al. "Big data in the construction industry: a review of present status, opportunities, and future trends". In: *Advanced Engineering Informatics* 30 (3 2016), pp. 500–521. DOI: 10.1016/j.aei.2016.07.001.

[48] Doroshenko, Anna. "Applying Artificial Neural Networks In Construction". In: *E3S Web Conf.* 143 (2020), p. 01029. DOI: 10.1051/e3sconf/202014301029. URL: https://doi.org/10.1051/e3sconf/202014301029.

[49] Ramon Elias Weber, Caitlin Mueller, and Christoph Reinhart. "Automated floorplan generation in architectural design: A review of methods and applications". In: *Automation in Construction* 140 (2022), p. 104385. ISSN: 0926-5805. DOI: https://doi.org/10.1016/j.autcon.2022.104385. URL: https://www.sciencedirect.com/science/article/pii/S0926580522002588.

[50] R. Larson. "Introduction to information retrieval". In: *Journal of the American Society for Information Science and Technology* 61 (4 2009), pp. 852–853. DOI: 10.1002/asi.21234.

[51] J. Jeon et al. "Extraction of construction quality requirements from textual specifications via natural language processing". In: *Transportation Research Record Journal of the Transportation Research Board* 2675 (9 2021), pp. 222–237. DOI: 10.1177/03611981211001385.

[52] J. Zhang and N. El-Gohary. "Semantic nlp-based information extraction from construction regulatory documents for automated compliance checking". In: *Journal of Computing in Civil Engineering* 30 (2 2016). DOI: 10.1061/(asce)cp.1943-5487.0000346.

[53] Wenming Wu et al. "Data-Driven Interior Plan Generation for Residential Buildings". In: *ACM Trans. Graph.* 38.6 (2019). ISSN: 0730-0301. DOI: 10.1145/3355089.3356556. URL: https://doi.org/10.1145/3355089.3356556.