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A Comprehensive Review of Artificial Intelligence Applications in Healthcare and Transportation

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ABSTRACT: In recent years, Artificial Intelligence (AI) has revolutionized numerous industries and become increasingly assimilated into society. Machine learning (ML) refers to the ability of systems to learn from training data and can be classified into three categories: supervised learning, unsupervised learning, and reinforcement learning (RL). ML, along with Deep learning (DL), a subset of ML based on neural networks, and Natural Language Processing (NLP), which enables machines to understand and generate human language, has played a pivotal role. This paper aims to provide a comprehensive review on the current state of AI by reviewing the applications of AI in the critical fields of healthcare and transportation, as well as the challenges associated with the rapid evolution of AI in these areas. Previous studies have contributed to the advancement of AI by thoroughly reviewing recent studies and innovatively applying ML, DL, and NLP technologies to solve specific problems. This literature review analyzes the previous studies that focus on healthcare and transportation while addressing the challenges and ethical concerns and proposing potential solutions. Findings reveal that AI technologies, particularly DL techniques such as Convolutional Neural Networks (CNN), have significantly surpassed human diagnostic accuracy in healthcare and optimized decision-making in autonomous vehicles (AV). The integration of Big Data and sentiment analysis has further advanced disease prediction and mental health research. Despite these advancements, challenges such as dataset variability, interpretability issues, and privacy concerns persist. Through the presentation and analysis of these findings, we intend to contribute to the understanding of the extensive impact of AI and shaping of AI technologies that can be ethically integrated into society.

KEYWORDS: Robotics and Intelligent Machines; Machine Learning; Healthcare; Transportation; Ethics.

Introduction

Artificial Intelligence (AI) seeks to imitate human behavior and efficiency in decision-making to solve complex tasks with little to no human input. Machine learning (ML), a subfield of AI, overcomes the limitations of early AI research, which was based on hard-coded statements. In ML, the computer program's performance improves with experience as it uses algorithms to learn from training data to find hidden, complex patterns without directly being programmed to do so.[1] Among the different types of ML, supervised learning and reinforcement learning (RL) are the main types that will be covered in the paper, as highlighted in various works.[1,2] While ML techniques can be applied extensively, the rapid evolution of digital technologies has resulted in the sheer magnitude of datasets surpassing the capabilities of these techniques, rendering them less effective.[3] Deep learning (DL) models, which are based on neural networks, have outperformed ML models in many instances, effectively navigating this challenge as it is able to analyze more complex and high-dimensional datasets.[1,3] Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) will be highlighted in this paper, as demonstrated by numerous studies.[1,3-5] The final subclass of AI that this review paper will explore the applications of is Natural Language Processing (NLP), which enables machines to interpret human language and convert it into a machine-readable format. Sentiment analysis and Big Data will also be discussed, as they intersect with NLP in the context of AI applications in healthcare and transportation, although the discussion of Big Data will extend beyond its application solely with NLP, as shown in previous research.[6,7]

These AI methodologies have become increasingly impactful in numerous key industries. While AI has impacted industries such as the finance, manufacturing, and marketing industries, we will focus on healthcare and transportation in this paper. While seemingly disparate, healthcare and transportation are immensely significant to society's progress and well-being, and AI has great potential to enhance them. For instance, in the healthcare industry, AI technologies are able to learn from large amounts of medical research and patient records in order to enhance doctors' decisions for diagnoses and treatments for patients.[8] In addition, DL is applied in the field of tumor pathology to assist in diagnosing tumors and identifying biomarkers and genetic changes.[9] DL is also utilized to classify lung nodules observed in computed tomography (CT) scans, where CNNs are employed to analyze 3D radiological images.[10] COVID-19, a disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), can be detected through the application of ML and DL techniques on chest CT scans, with several studies yielding highly accurate results. Big Data can help in vaccine discovery and drug development for COVID-19, as well as forecasting the global impact of the pandemic.[7] Progress in the Big Data field has motivated healthcare professionals to collect data from media platforms and utilize sentiment analysis to analyze patients'

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writings and facial expressions. This aids in gaining insights into patients' mental well-being.[6] AI advancements have also revolutionized the transportation industry by implementing DL techniques for road network planning, predicting traffic conditions, incident detection, autonomous vehicles (AVs), and public transport systems. In Intelligent Transport Systems (ITS) technologies that aim to lessen traffic jams and enhance the driving experience, Deep Reinforcement Learning (DRL) has been employed to optimize traffic control strategies in real time across large-scale ITS. Additionally, DRL has found application in driving scenarios where traditional supervised learning approaches are no longer feasible.[2,5]

This paper will evaluate the current state of AI technology by exploring both empirical and review papers regarding AI in healthcare and transportation. By delving into studies concerning these topics, this paper aims to guide future research into overcoming current challenges and ethical concerns, such as training DRL in autonomous driving as the agent often resorts to learning from collisions, social acceptance of AVs, bias, privacy, and responsibility for medical failures.[4,5,8,11] Considering the potential benefits of AI in reducing car ownership and CO_2 emissions through AVs, and improved disease treatment and detection, it is crucial to take into account the challenges and ethical concerns for AI to reach its full potential without the drawbacks outweighing these benefits.[5,8] In the next sections, we will first conduct a literature review to highlight the methodologies that recent studies have used. Then, we will discuss the applications of AI in the healthcare industry, focusing on AI's role in pathology, radiology, and psychiatry. This will be followed by a deeper dive into ANN, CNN, and DRL applications of AI in transportation. Afterwards, we will address current challenges, ethical concerns, and potential solutions, and finally, provide a summary of the content reviewed to conclude this paper.

Literature Review

An analysis of recent literature reveals overarching trends in the methodologies used in these studies. This literature review will explore these trends by categorizing studies based on their application of specific AI technologies in both healthcare and transportation. Through systematic categorization, this review aims to identify patterns in healthcare and transportation methodologies. These trends reveal the causes of gaps in current research and underscore the importance of understanding the methods employed to advance knowledge of AI application in the fields of healthcare and transportation. The dynamic nature of research methodologies reflects the ongoing search for innovative solutions to complex problems. Additionally, comparing trends between healthcare and transportation methodologies can provide valuable insights into cross-disciplinary applications. For instance, a methodology proven to be effective in healthcare may offer innovative solutions to challenges in transportation. By conducting a literature review focused on studies that explore AI implementation in healthcare and transportation, the current state of the literature can be evaluated thoroughly. To interpret the implications of these studies, it is essential to understand core AI concepts, which provide the foundation for these research methodologies. Table 1 highlights AI concepts and studies alongside the AI concept that they apply to healthcare or transportation.

Table 1: Overview of AI concepts and key studies in healthcare and transportation.

Concept	Description	Key Studies
Supervised learning	Supervised learning uses a training dataset with input and labeled output or target values, and these models can be used to predict outputs for new inputs once trained.[illegible]	Williams Zhang and Cho Roy et al.
Reinforcement Learning	An RL system employs an agent that is given the current state of the system and a goal instead of input and output values, and the agent is required to represent its environment while acting optimally, maximizing reward through trial and error.[illegible]	Wulfmeier et al. Abdellatif et al.
Artificial Neural Networks	Neural Networks are designed to mimic the way a human brain operates.[illegible] In Artificial Neural Networks (ANN), processing units known as artificial neurons are connected like synapses in a brain, and the weight of these connections can be adjusted throughout the learning process in order to control the strength of the signals passed through them. These neurons are grouped in distinct layers: input layers, output layers, and hidden layers that learn a non-linear mapping between the input and output layers.[illegible]	Doğan and Akgüngör Alshanbari et al.
Convolutional Neural Networks	Convolutional Neural Networks (CNN) are a type of ANN that excel in image processing.[illegible] Typically organized into layers, CNNs consist of convolutional and pooling layers in the lower levels of the networks, followed by fully connected layers in the higher levels. Convolutional layers extract basic features for input data using edges and corners and apply filters to reduce complexity, while pooling layers decrease the dimensionality of the result, combating overfitting. Fully connected layers, situated after the convolution and pooling layers, learn deeper representations, and the final layer uses a loss function to map inputs to their respective outputs.[illegible]	Bojarski et al. Setio et al.
Sentiment Analysis	Sentiment analysis utilizes a variety of techniques, including NLP techniques. Sentiment analysis uses NLP techniques to interpret and associate emotions conveyed within text gathered from multiple sources.[illegible]	Rajput Gohil et al. Ricard et al.
Big Data	Big Data refers to the vast amount of data that can be generated by multiple sources, including online social graphs, mobile devices, Internet of Things (IOT) devices (i.e. sensors) and public data. It is characterized by volume, variety, and velocity, which is essentially referring to the vastness of data, the format and structure type of the data, and the speed of data generation. The Big Data field encompasses concepts from NLP, thus influencing the way scientists approach problems related to this field, and also includes concepts from ML, Information Retrieval, etc.[illegible]	Pham et al. Sazu and Jahan

Williams described a methodology to predict turbulence in aviation using data fusion, which is trained using a dataset that combines past turbulence reports from commercial aircrafts and related predictor data. The prototype combines information from Doppler radar, satellites, a lightning decision network, and a weather prediction model.[12] Zhang and Cho discussed the usage of supervised learning to train a policy function to imitate a reference policy, which is typically a car that is driven. By collecting state observations and corresponding actions from the reference policy, a dataset is formed. Then, a loss function is defined to measure the difference between the actions predicted by the primary policy and the actions taken by the reference policy. The primary policy is trained to minimize this loss function using the collected dataset. However, it is noted that purely using supervised learning may lead to suboptimal results, which transitions to the discussion of going beyond supervised learning.[13] A more recent review by Roy *et al*. examined the existing literature to understand the current state of supervised learning in healthcare, highlighting its potential to improve disease diagnosis, enhance personalized medicine approaches, optimize clinical trials, facilitate non-invasive image analysis, accelerate drug discovery processes, improve patient care services, enable remote patient monitoring, leverage hospital data, and enhance nanotechnology applications.[14] Collectively, these diverse applications of supervised learning highlight its versatility in solving complex problems in healthcare and transportation, even though there are limitations. The similar approach of creating datasets using data collected in both Williams' and Zhang and Cho's described methodologies demonstrates how the accuracy of supervised learning models can be maximized by leveraging high quality, diverse, and relevant data.

Wulfmeier *et al*. utilized Inverse Reinforcement Learning (IRL) to produce a scalable model based on a Maximum Entropy non-linear framework as it can continue to run despite dataset extent during deployment. They utilize a dataset with 25,000 demonstration trajectories that were collected over 120 kilometers of driving around pedestrianized areas.[15] Abdellatif *et al*. review RL models that have been developed for Intelligent-healthcare (I-health) systems. They discuss how RL can benefit I-health systems by looking at the structure of I-health systems and current challenges.[16] The studies conducted by Wulfmeier *et al*. and Abdellatif *et al*. reveal the trend of RL techniques being tailored to address gaps in research in specific domains of both healthcare and transportation.

Doğan and Akgüngör used an ANN model with sigmoid and linear activation functions combined with feed-forward back propagation to evaluate the effect of railway development on highway safety and highway casualties. This experiment is also approached with the application of a non-linear multiple regression model.[17] Alshanbari *et al*. used an ANN model to predict death counts and recovery of patients due to COVID-19. They compare the accuracy of this ANN model with the accuracies of five univariate time series models.[18] The studies conducted by Doğan and Akgüngör and Alshanbari *et al*. highlight the trend of using ANN models for prediction of real-world outcomes, such as death count. Additionally, both of these studies compared the ANN model they proposed to other types of models. These similarities in methodologies despite the difference of the industries that these studies impact suggest that ANN solutions that are effective in healthcare may also be effective in transportation, and vice versa.

Bojarski *et al*. used CNN by training the model with minimal training data from humans. Instead, the model learns to drive in traffic on local roads on highways with a single front-facing camera that uses image data as input to output steering commands for autonomous driving. The representations that the model must learn are not predefined, but rather, the model self-optimizes all processing steps at the same time.[19] In contrast to the single front-facing camera approach that is utilized in this study, Setio *et al*. uses multi-view CNNs for lung nodule detection in order to reduce false positives. The network takes in input from three candidate detectors and extracts 2-D patches from differently oriented planes for each.[20] The studies conducted by Bojarski *et al*. and *Setio* e*t al*. demonstrate that CNNs applied to both healthcare and transportation, albeit in different ways depending on the environment and goal in order to maximize accuracy. While CNN models that process tasks in a unified manner in order to autonomously adapt are suitable for the dynamic environment in autonomous driving, CNN models that handle comprehensive data from multiple perspectives separately and combine the data are better suited for optimizing accuracy in healthcare, where the environment is typically more stable. However, in both studies, CNNs are applied innovatively, suggesting that future research will continue to explore versatile applications of CNNs across various fields.

Rajput reviewed the applications of sentiment analysis and NLP in mental health, as well as the relevant NLP theories that can be used to analyze user sentiments on social media.[6] Gohil *et al*. conducted a literature review of 12 papers studying the qualitative measurement of sentiment in health care, specifically on sentiment analysis on tweets from Twitter. This study compares the types of tools used in the reviewed literature and methods for producing these tools.[21] Ricard *et al*. used a Web-based survey to collect Instagram and Patient Health Questionnaire-8 (PHQ-8) scores, with features such as sentiment scores and emoji sentiment analysis results extracted from post captions and comments for predictive modeling. They compared models that predicted PHQ-8 scores for detecting depression trained on user-generated data with models trained on community-generated data.[22] These studies reveal the growing interest in sentiment analysis in conjunction with NLP techniques. Additionally, the studies conducted by Gohil *et al*. and Ricard *et al*. display the importance of abundant social media data and suggest that with the growth of Big Data, the potential for more advanced and nuanced analyses in healthcare and mental health research continues to expand.

Pham *et al*. examines the role of Big Data in preventing the negative effects of COVID-19 by providing an overview of Big Data and highlighting applications aimed at combating COVID-19, such as medical imaging processing and smart devices with AI frameworks.[7] Sazu and Jahan conducted a literature review on big data analytics for smart commuter route programs and proposed a comprehensive framework for improving transportation efficiency and reducing congestion. The literature evaluation employed a systematic process to analyze scientific studies, aiming to minimize bias and ensure reproducibility. Using the Web of Science database, a search was conducted for papers related to "big data" and "smart transportation infrastructure" from 2015 to February 2022, resulting in 231 files, with 201 shortlisted for further examination to identify patterns, mathematical models, and real-world applications in the context of smart commuter route systems.[23] In both of these studies, literature reviews of Big Data in the context of specific applications were conducted, demonstrating the breadth of research and practical applications within the field. Furthermore, both studies exemplify a rigorous and systematic approach to data analysis, which underscores the importance of methodological robustness when discussing Big Data.

Overall, this literature review has evaluated the current state of AI in healthcare and transportation, setting the stage for the next section. In the subsequent section, we will discuss the applications of AI in healthcare, followed by the discussion of the applications of AI in transportation.

Discussion

1. AI in Healthcare:

In this section, we will discuss the current applications of AI in healthcare, highlighting its utilization and potential for

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medical diagnosis, prognosis, and assistance in fields such as pathology, radiology, and psychiatry. AI technologies have been adopted by numerous healthcare institutions in recent years to improve patient care and enhance medical tools. For example, the medical professionals at Moorfield's Eye Hospital in London have created an AI diagnosis system capable of suggesting treatments for over 50 eye diseases with an accuracy of 94%, while the Mayo Clinic organization from the US has utilized AI to detect precancerous anomalies in a woman's cervix with an accuracy of 91%, which surpasses human professionals' accuracy of 69%.8 Evidently, AI has aided in exceeding the limitations of human assessment.

Another instance of AI demonstrating this capability is in tumor pathology, where AI can help pathologists differentiate between tumors and other lesions and classify them as cancerous or non-cancerous. With increasing usage ever since the introduction of whole-slide scanners in 1999 and establishment of extensive digital-slide libraries, AI overcomes the challenges posed by visual evaluations conducted by pathologists and allows for more precise tumor treatments.[9] There has also been a rise of interest in the applications of AI in radiology, particularly CNNs for lesion detection, classification, and segmentation, which are implemented in CT scans that detect diseases such as cancer and COVID-19.[7,10] COVID-19 affected over 200 countries worldwide, calling for a global pandemic in which lockdowns of infected areas, as well as wearing masks and social distancing in public, became common practices. As such, the applications of AI to combat this disease extended beyond a radiological scope to provide more assistance to doctors during the crisis.[7] AI utilizes data from open-source datasets and media platforms to do this, and this capability is what has sparked the interest of psychiatrists and psychologists alike to transition from the traditional approach of gathering information through questionnaires filled out by patients or people belonging to certain groups to using AI to overcome the obstacle of inability to obtain data that accurately represents a patient's mental state.[6,7] As we delve further into the role of AI in healthcare, we will first discuss its impact in pathology and radiology.

1.1 AI Applications in Pathology and Radiology:

AI applications in both pathology and radiology can identify different types of cancers and have the potential to do exceedingly well in disease detection and enhancing patient treatments, as demonstrated by numerous studies and experiments.[9,10] In tumor pathology, DL approaches have been found to be more efficient than traditional hand-crafted ML models, which do not have as high of an accuracy rate and are harder to perform.[9] Additionally, recent studies in radiomics use hand-crafted feature extraction techniques and traditional ML classifiers. CNNs do not need hand-crafted feature extraction or manual segmentation of tumors and organs.[10] Therefore, they can be used in radiology and pathology to optimize results, as demonstrated by a study conducted in 2018 that utilizes CNN to analyze stroma features in order to classify stroma surrounding cancerous growth and stroma found in benign biopsies. This study involves the usage of medical records, self-reported information about breast cancer risk, donations of saliva and blood, and authorization to access radiological images and pathological tissues of 882 women of ages 40-65. The first CNN model that classified whole-slide images epithelium, stroma, and fat achieved an accuracy of 95.5% when compared with reference standard, while the second model that classified standard stroma and stroma associated with tumors achieved and accuracy of 92.0% when compared with reference standard.[24]

Generally, CNNs in pathology are utilized by first having tissue slides undergo a conversion process into whole-slide images using digital scanners. Then, features are extracted patch-by-patch and designated for classification, contributing to the development of diagnosis and prognosis models. Figure 1 provides a visual representation of feature learning and classification through CNNs, illustrating how image patches from whole-slide images undergo convolution and pooling, and are then fed into neural networks with input, output, and hidden layers. From there, a diagnosis can be made that includes whether a tumor is malignant or benign and low-grade or high grade, as well as non-small cell and small cell when diagnosing lung cancer. Additionally, the prognosis can be determined, which includes the forecasting of the probability of survival for a patient over a period of time.[9]

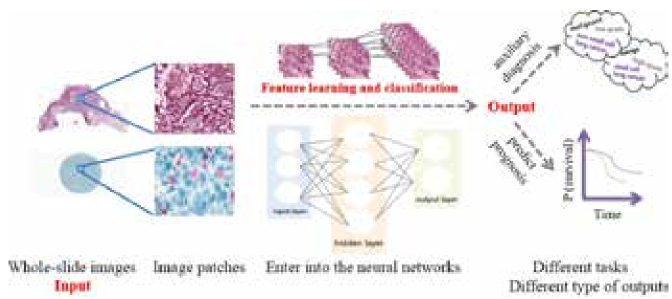

Figure 1: Typical sequence in employing deep learning-based algorithms on pathological whole-slide images.[9]

While CNNs demonstrate the ability to optimize the analysis of tissue slides in pathology, their practical application in radiology introduces complexities as neural networks designed for 2D images cannot be applied to 3D images obtained through CT scans. Instead, unique approaches are applied.[10] For example, a study conducted in 2016 uses multi-view CNN to categorize lung nodule candidates in chest CT images as either nodules or non-nodules within the available Lung Image Database Consortium and Image Database Resource Initiative (LID-IDRI) dataset, achieving a sensitivity of 94.4% when combining the three algorithms.[20] AI implementation through CT scans not only shows promise in detecting lung cancer, but also in detecting COVID-19. An experiment applying CT scans conducted in 2020 achieved an Area Under Curve (AUC) score of 0.994 when classifying COVID-19 patient data from Zhejiang, China.[25] With AI reshaping both pathology and radiology, the integration of Big Data becomes crucial to enhance applications not only in the fields discussed that involve disease detection, but in other fields as well.

1.2 AI Applications in Psychiatry and the Integration of Big Data:

Psychiatry is one of the fields in which AI has the capability to transform traditional methods through the utilization of Big Data. Big Data integration is not limited to psychiatry, and it can be applied to the AI applications that assist in combating the diseases that were previously discussed, such as COVID-19. When referring to 'Big Data' in the context of COVID-19, it encompasses details such as physician's notes, X-ray reports, case history, lists of healthcare professionals, and data related to outbreak areas. Utilizing models derived from extensive datasets not only facilitates the prediction of future COVID-19 outbreaks through its capacity of clustering substantial amounts of data for early detection but also enables large-scale investigations leveraging diverse real-world sources. This approach contributes to the development of thorough and highly reliable treatment solutions, which can be developed at a faster rate than normal by speeding up drug testing at rates that a human may not be able to perform themselves. The monitoring of different regions using media sources helps ensure that people who reside in vulnerable areas can take proper preventive measures. Additionally, it aids healthcare providers in gaining insights into the overall nature of virus development, enhancing their ability to respond effectively to various treatment and diagnostic challenges.[7,26]

In psychiatry, sentiment analysis, which utilizes Big Data and NLP techniques, can be used to discern the true meaning behind a patient's writings on social media through analysis of tone and context. To do this, the writing is first broken down into words and sentences through preprocessing and tokenization. Lexical analysis involves dividing the text into lexemes, which are root words that have various forms with different endings, by minimizing each token into its unit token form. An example of a unit token is the word "sleep", which can have various forms such as "sleeping" and "sleeps". In addition, syntactical analysis ensures that the text follows grammatical rules and makes sense, while semantic analysis analyzes the meaning of the text in the given context. NLP and sentiment analysis are just starting to penetrate the fields of social sciences and medicine, and they provide numerous opportunities for applications in mental health.[6]

1.3 Future Directions for AI in Healthcare:

The applications of AI in pathology, radiology, and psychiatry demonstrate incredible ability in enhancing healthcare. The success of DL techniques, particularly CNNs, in pathological studies showcase this ability, while its applications in radiology introduce new complexities involving 3D CNN CT scans that thorough studies have combated efficiently.[9,10] This highlights the potential and benefit of further research for improving AI applications in these fields. The technologies refined in disease diagnosis and prognosis, such as AI applications for COVID-19, can be applied to many other diseases in the future epidemics and pandemics.[26] Moreover, Big Data opens up possibilities for AI assistance in healthcare in both disease prediction and psychiatry, with the latter focusing on sentiment analysis in the field of mental health.[6,7]

The discussion about recent applications and advancements in these fields of healthcare offers significant research objectives for future study, such as further optimizing 3D CNNs for handling radiological images, with one method being comparison between different optimization techniques from various studies. Another noteworthy objective is the application of AI in rare diseases, as there are about 6000-8000 known ones.[8] By using the technologies developed for cancers and COVID-19, researchers can create more generalized models or modify current models to perform optimally for different groups of rare diseases. Ultimately, AI offers multitudinous opportunities for the refining and optimization of the healthcare industry. It is important to note that while the impact of AI extends beyond healthcare, as exemplified by the next section, it is essential to consider the challenges and ethical concerns that are discussed in this paper as well.

2. AI in Transportation:

AI plays a significant role in transportation, and advancements in this area, such as those in autonomous driving, could lead to AVs becoming an efficient mode of transport in the future. Addressing the challenge of unpredictable travel patterns of users is difficult when paired with factors such as the growing demand for travel, CO_2 emissions, safety issues, and environmental harm. Therefore, AI can help resolve these issues, which stem from population growth in developing countries that contributes to an increase in traffic in rural and urban areas. For example, Australia's congestion cost is estimated to rise to 53.3 billion by 2031, with CO_2 emissions in Melbourne accumulating to 2.9 tons per year. AVs can be beneficial in these kinds of places. They are also expected to reshape travel patterns to change social structures and urban layouts, aiding in car and ride sharing to address issues of accessibility and reliability.[5]

Though the prospect of integrating AVs into our lives in all conditions seems out of reach, the development of AD in recent years, including the shift from testing AVs in labs to driving on public roads and companies such as Tesla and Waymo leading these advancements, encourages researchers to strive to establish a reliable transport system to reach this goal.[4,5,8,11] These AVs process data that come from multiple present sources, such as cameras, LiDARs (Light Detection and Ranging), radars, ultrasonic sensors, GPS units, and inertial sensors. Similar to its purpose in AI technologies for healthcare, CNNs are essential to object detection as they can help AVs distinguish other vehicles and roads safe to drive on even in urban areas where many objects and blockages may appear.[11] Researchers have utilized this algorithm for analyzing 2D images and 3D point clouds from cameras, as well as ANNs for numerous tasks such as predicting incidents, conditions, and optimal routes.[5,11]

Figure 2 provides a visual representation of ANN use for predicting future traffic states by taking in input from both upstream and downstream the target location in order to incorporate the conditions that may influence the upcoming traffic conditions and the effects of the conditions past the target location. The speed of which the vehicles are moving, the occupancy, and the flow of traffic at a certain point in time

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are the inputs that hidden layers recognize patterns from, and the network outputs the future traffic state.[5] The role of ANNs and CNNs will be further elaborated on in subsequent passages in this section. Afterwards, we will discuss the function and benefits of DRL systems in AD, which can make complex decisions using the driving policy produced by the decision-making system, trajectory planning that steers the agent on an optimal physical path, and controllers that are responsible for speed, braking, and acceleration.

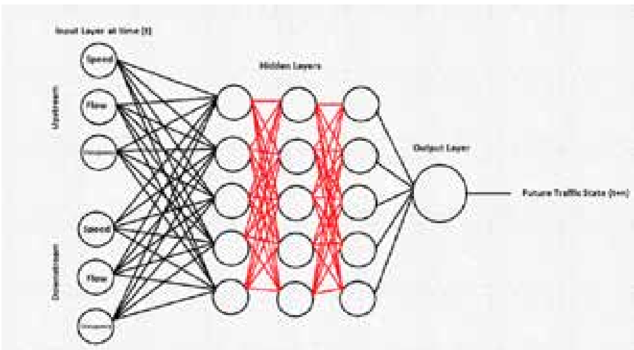

Figure 2: Representation of DL system utilization for predicting future traffic state.[5]

2.1 Neural Networks for Transportation Planning and Decision-Making:

The integration of AI, particularly neural networks, has been instrumental in transportation planning and prediction for decision-making. The purpose of planning is to recognize the community's requirements and determine the most effective strategy to meet them while taking into account the social, environmental, and economic factors on transportation. Numerous studies have been conducted to design and model roads using neural networks.[5] 'Planning' can also be seen in the context of analyzing historical data to make informed decisions. An example of this can be seen in a study conducted in 2013, where historical data spanning 27 years (1980-2006) was used to explore the relationship between Transportation System Usage Percentages (TSUP) and traffic accidents and injuries in Turkey. ANNs outperformed other models in this study, which highlights their efficiency and reliability. In the context of Turkey's railway investments, three distinct scenarios were developed, each considering different trends in TSUPs. In Scenario I, where there is no major shift from highways, the prediction indicates a significant increase in the number of accidents and injuries over the period of 2006–2020. On the contrary, Scenario II, which involves an increase in railway investments, predicts a reduction in accidents and injuries compared to Scenario I, highlighting the positive impact of railway investments. Scenario III, representing slightly less railway investments, shows intermediary results between Scenarios I and II, indicating a nuanced outcome in terms of accidents and injuries. These can be used to strategically plan transport investments in Turkey, which would benefit the country since it is a developing nation.[19]

As evidenced by the study, using data from the real world is beneficial for training and testing, and this can also help develop components of AVs. Data collection from public roads can provide AVs with the necessary high amount of data. Equipped with multiple sensors, they can get a broad view of the driving scene around them. End2End Learning Control refers to the direct mapping from sensory data to control commands, typically utilizing inputs from high-dimensional feature space.[11] A study conducted in 2016 uses End2End to train CNNs to map raw pixels directly to steering commands. Data collection involved diverse driving conditions, such as a variety of roads, lighting, and weather, and the CNN architecture comprised 9 layers. Training focused on frames where the driver remained in the lane, with data augmentation to enhance recovery from poor positions. Simulation tests showed the CNN achieved about 98% autonomy during on-road tests, displaying robust performance even on local roads and highways. The study concludes that CNNs can effectively learn the entire task of lane and road following with minimal training data, suggesting potential advancements in autonomous driving systems.19 DRL can also be used as an approach to End2End driving systems.[11] But while CNNs are proficient in learning tasks such as lane and road following through end-to-end mapping, DRL outperforms classical supervised methods such as these when other aspects to AD are introduced.[2]

2.2 Deep Reinforcement Learning for Navigating Dynamic Environments:

DRL plays a crucial role in enhancing autonomous driving systems by enabling agents to anticipate the impact of their future actions on sensor observations. This capability is particularly valuable for tasks like determining optimal driving speed in urban areas, where dynamic scenarios and changing conditions require adaptive decision-making. DRL accommodates supervisory signals such as time to collision (TTC) and lateral error, handling scenarios with stochastic cost functions and environmental uncertainty effectively. The agent learns to maximize these stochastic cost functions, allowing it to respond adeptly to dynamic situations and uncertainties. In high-dimensional spaces with numerous unique configurations, DRL excels at learning and representing the environment, navigating this large space by making optimal decisions at each instant referred to as 'policy'. While supervised learning relies on labeled image datasets, DRL necessitates an environment for recovering state-action pairs and modeling the dynamics of vehicle state and environmental interactions, accommodating stochastic movements. Simulators play a crucial role in training and validating DRL algorithms, simulating various sensors like cameras, LiDARs, and radar. Driving policies acquired through learning undergo rigorous testing in simulated environments before advancing to expensive real-world evaluations.[2] Continuous control with DRL is possible, but the most common approach is discrete control.[11] The role of DRL will increase in the future, especially as data complexity increases as ITS systems continue to advance. Since DRL can be applied to ITS effectively, they will be imperative for finding complex patterns to ultimately facilitate the realization of more interconnected transport systems.[5]

2.3 Future Directions for AI in Transportation:

DL approaches to transportation such as ANNs, CNNs, and DRL display high potential for revolutionizing the trans portation industry. Advancements achieved by utilizing these algorithms are evidence of this, suggesting that though AD seems unreachable, further research can enable the optimization of these techniques while considering the impact on society.[4,5] ANNs can be used for designing and modeling roads in transportation planning. They are also employed in analyzing historical data to make informed decisions.[5,17] CNNs, on the other hand, are efficient in tasks such as lane and road following, object detection, and analyzing images from various sensors.[11,19] DRL plays a crucial role in enhancing AD systems by enabling agents to make decisions in dynamic and uncertain environments. It is used for tasks such as determining optimal driving speed in urban areas and handling scenarios with stochastic cost functions.[2]

Researchers can investigate how to improve DRL systems so that they can be used for continuous control, aiding in the development of reliable Avs.[11] Additionally, they can use Big Data to apply ANNs in other areas, utilizing real-world data to advance AI in transportation.[5] CNNs can be improved to handle more dynamic situations as well, and researchers can integrate real-world datasets that have more diverse data with numerous occlusions.[11,19] In summary, the integration of AI technology is positioned to bring transformative advancements to the transportation industry. However, challenges and ethical concerns must be taken into consideration to do this, which will be discussed in the following section.

3. Current Challenges, Ethical Concerns, and Potential Solutions:

While the previous sections highlighted the benefits of AI technology being integrated into the healthcare and transportation industries, it should not create the illusion that AI is currently socially accepted by all and presents no technical challenges. This section will focus on the inherent ethical challenges and technical problems of AI within these industries, proposing future directions and potential solutions. Policymakers and professionals have sought strategies to address the ethical challenges linked to AI advancement. Instances of guidelines and regulations include the European Commission's "Ethics Guidelines for Trustworthy AI", the US "Report on the Future of Artificial Intelligence", and the Chinese government's "Beijing AI Principles". However, difficulties arise when considering questions regarding responsibility, bias, security, and privacy, and the policies for AI regulation are unable to keep up with the speed at which technologies advance at. Furthermore, AI-based technologies need to possess adaptability in problem-solving and align with human-oriented values.[8,27] The rest of this section will discuss ethical concerns and practical challenges in a systematic manner according to the sequence of topics discussed previously, beginning by examining the challenges posed by AI in the healthcare industry and subsequently shift focus to the transportation sector.

3.1 Challenges of AI Implementation in Healthcare:

Current AI models in pathology primarily rely on limited datasets and images obtained from a single source. However, even with efforts to enhance the dataset through techniques such as random rotation, flipping, color adjustments, and Gaussian blur, there remains variation due to differences in slide preparation, scanner models, and digitization across different centers. To combat this, leveraging large-scale digital-slide libraries like TCGA for training or validating datasets is possible, and the development of these AI technologies can be aided by the constant validation of diagnoses by expert pathologists as well. Curated whole-slide imaging reference datasets covering various cancer subtypes with annotated cancerous regions can be used, also facilitating the standardized evaluation of AI algorithms.[9] During the COVID-19 outbreak, issues regarding datasets arose as well since there was a lack of standard datasets. Researchers mostly collected available datasets from the Internet and combined them for use. The issue can be resolved by government and health organization efforts to provide a variety of data, which would help in future epidemics as well.[7]

Furthermore, the issue assigning responsibility is a large one in the field of AI. To give an example, it can be difficult for pathologists to describe the diagnostic evidence from an AI report, and they struggle with assigning responsibility when AI aids in creating a diagnostic report. The “black box” nature of AI, which refers to the difficulty of understanding how an AI system arrived at a decision, causes a lack of interpretability, lowering the confidence of doctors and patients in AI technologies.[9,27] This is also an issue in radiology, and there has been work done to combat this in both fields, such as methods to integrate DL algorithms and hand-crafted ML models and to visualize feature maps.[9,10]

In psychiatry, an issue that psychiatrists and psychologists are actively trying to combat is the use of emojis, various languages, and non-standard words in media, which limits AI technology in this area.[6] Privacy concerns emerge as well when collecting personal information, which was done during the COVID-19 pandemic and is done in sentiment analysis that utilizes data from social media as well.[6,7] Potential solutions include strict guidelines for the security and acquiring of data, secure storage and transfer of data within regulatory bounds when developing AI solutions in healthcare, and the ensuring of ethical approval and patient consent for data transmission.[27] In the transportation industry, many ethical challenges that arise are similar to those of healthcare, and thus have similar solutions in many cases. As such, the ethical challenges that will be discussed in the following passage will be different from the ones that have already been discussed in the context of healthcare, though these challenges may apply to healthcare as well (e.g. safety). The technical challenges of AI in transportation differ from those of healthcare as well, which will also be discussed in the following subsection.

3.2 Challenges of AI Implementation in Transportation:

One of the central challenges regarding AI in the transportation industry is safety and social acceptance. People are generally more interested in the ability of vehicles to recognize and correct mistakes they make and interact with humans using natural language than self-driving technology.[5] If not handled correctly, the deployment of AVs in real environments could be dangerous, especially if this occurs right after the training process.[2] The issue stems from the tendency for DRL to have biased behavior in the real world even though they are

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able to navigate different situations in simulations. DRL being applied to continuous control is less common than discrete control because the agent resorts to learning from collisions in simulations since it needs to explore its environment, which is what introduces bias in real world situations. A potential solution for this is the usage of IRL, which can allow AVs to learn from human driving demonstrations rather than learning from unsafe actions.[11] For imitation learning-based systems, SafeDAgger presents a safety policy that is designed to forecast errors made by a primary policy. This primary policy is initially trained using a supervised learning approach, and notably, SafeDAgger achieves this without the need to consult a reference policy.[2]

In addition, a significant challenge regarding the DRL training process arises when it requires too many samples to learn a reasonable policy. A potential solution to combat this is reward shaping, which allows the agent to acquire intermediate goals through the creation of a more regular reward function. This approach aims to expedite the learning process for the agent, enabling faster acquisition of knowledge from a reduced number of samples.[2] Discrepancies in the reward function, however, can have adverse impacts on the trained model. For example, the AV may discover a way to evade penalty for driving too closely to other vehicles by exploiting specific vulnerabilities in its sensors, hindering its ability to accurately gauge proximity. An essential aspect of evaluating the safety of deep learning components involves assessing whether the immediate human consequences of outcomes surpass certain thresholds for the severity of harm. There is no definition of 'safety' agreed upon in the context of ML and DL, which is something that needs to be rectified in order to apply this.[11] If standardized frameworks and guidelines were developed for AI implementation in transportation, as it is in healthcare, such as the Clinical Laboratory Improvement Amendments (CLIA), among other clinical guidelines, then AI technologies could be developed under trusted frameworks.[9]

Conclusion

This paper has delved into the transformative impact of AI in healthcare and transportation, highlighting applications, advancements, and associated challenges. It was argued that AI has the potential to revolutionize healthcare diagnostics and disease detection, as well as play a crucial role in transportation planning and autonomous driving. The literature review highlighted the current state of AI in healthcare and transportation, identifying trends in the methodologies. The discussion on AI in healthcare emphasized its significant role in pathology, radiology, and psychiatry. In pathology, DL techniques are incredibly efficient in tumor diagnosis, surpassing traditional models in accuracy.[9] AI applications in radiology, particularly CNNs, have shown promise in lesion detection and disease diagnosis through methods like CT scans.[7,10] The integration of Big Data in healthcare, especially during the COVID-19 pandemic, has enhanced disease prediction, and through sentiment analysis, psychiatry applications as well.[6,7] In transportation, AI's role in AVs and traffic planning has been explored as well. Advanced algorithms like CNNs and Deep Reinforcement Learning (DRL) contribute to object detection, route optimization, and decision-making in Avs.[2,5] Neural networks, including Artificial Neural Networks (ANNs), have been instrumental in transportation planning by analyzing historical data and making informed decisions.[5,17] However, the integration of AI is not without challenges and ethical concerns. In healthcare, issues like dataset variability, interpretability, and the "black box" nature of AI pose challenges.[9,27] Transportation faces challenges regarding safety, biased behavior, and the need for a universally agreed-upon definition of safety.[2,5,11] In the face of these challenges, ongoing research and collaborative efforts are essential. Ethical guidelines and regulations, such as the European Commission's "Ethics Guidelines for Trustworthy AI," aim to address concerns of responsibility, bias, security, and privacy.[27] Technical solutions, including curated datasets, improved interpretability, and innovative AI algorithms, can mitigate challenges in both healthcare and transportation.[2,9,10]

As we look to the future, key questions arise. How can AI be further optimized to handle the complexities of pathology and radiology in healthcare? Can DRL in transportation be extended to continuous control, making AVs safer and more reliable? These questions point to areas for future research and development.

In conclusion, while AI presents immense opportunities for advancements in healthcare and transportation, we must carefully consider the challenges and ethical implications. Research that adheres to this will shape the future of AI in these industries, unlocking the full potential of AI for the benefit of society.

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