NCHRP Project 23-16

Implementing and Leveraging Machine Learning at State Departments of Transportation

Briefing Document
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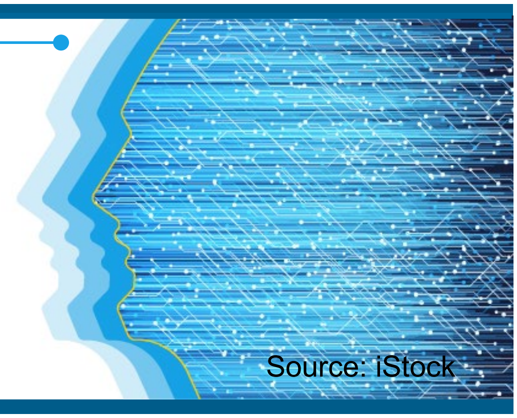
Machine Learning at State Departments of Transportation: Briefing Document

Supplement to the NCHRP Project 23-16 Final Report



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ML Overview: *Why consider ML?*

What is ML? Machine Learning (ML), a subfield of Artificial Intelligence (AI) (Figure 1), refers to the field of study of algorithms that learn complex patterns from data or previous examples. Instead of relying on rules-based programming, where a programmer tells the algorithm what to do in certain situations, ML algorithms discover patterns through a model training process. When done correctly, this allows models to extract insights, find correlations among variables, predict likely outcomes from given inputs, find optimal strategies for decision-making, and more. By adapting to and retraining on new data, ML models can improve their performance over time without human intervention.

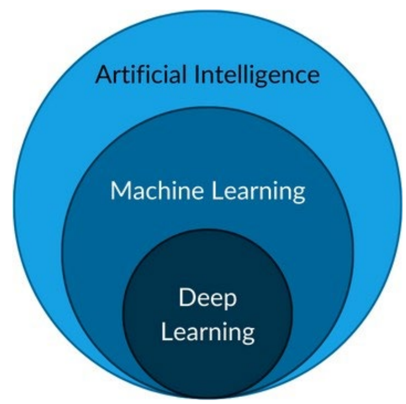

Figure 1. Universe of Artificial Intelligence

Methods that may be considered part of ML span a wide array of models, assumptions, and complexities. For example, a technique as simple as linear regression may be considered ML. This technique prioritizes interpretability and understanding of relationships between variables. On the other end of the spectrum, models categorized under deep neural networks (deep NN) can be extremely complex, with billions of parameters. Deep NN models have evolved rapidly over the last decade and have shown major breakthroughs in image, video, sound, and text processing. Some of these architectures can now outperform humans in various board or video games, as well as in image and object recognition (Silver et al. 2017, Payghode et al. 2023, and Purves 2019). This rapid advancement has led to the adoption of ML techniques across fields and sectors.

How is ML different from other methods? ML models differ from other programming paradigms and statistical models. In traditional statistical models, the focus is on understanding relationships between variables or making inferences about some parameters of interest. ML models, on the other hand, are optimized to make the most accurate possible predictions when given new data – data that the model has not yet seen or been trained on. The model training process involves tuning the model to find the set of parameters that produces the best results when applied to new data.

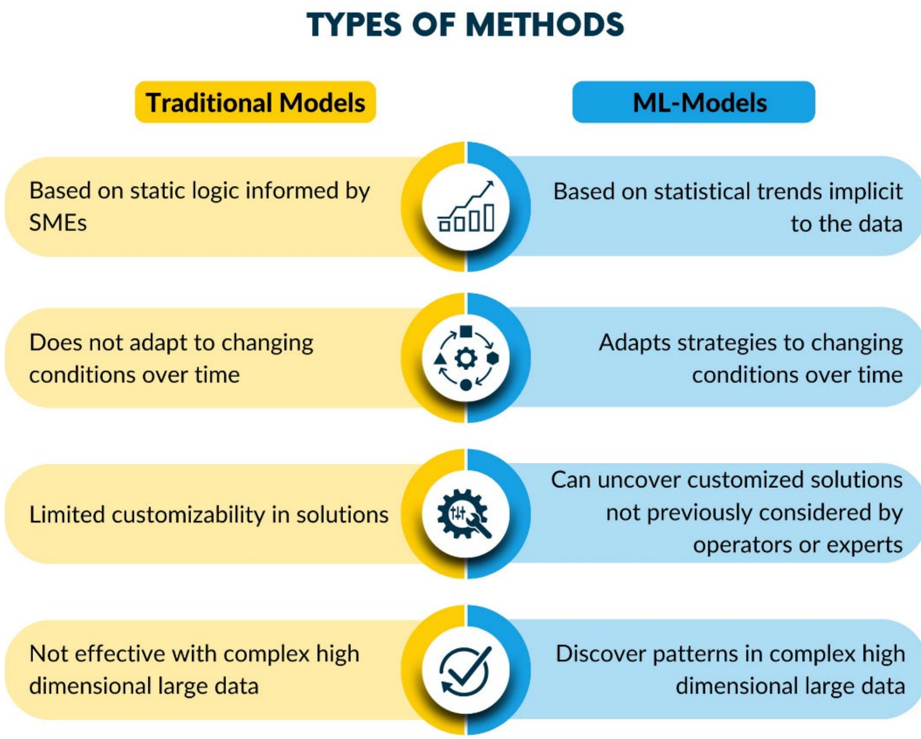

FIGURE 2. COMPARISON OF TRADITIONAL MODELS AND ML MODELS

Figure 2 shows several key aspects distinguishing ML models from more traditional models:

- *Learning from data:* Traditional models assume a fixed form (e.g., a linear relationship) and fit the data using those assumptions. ML models can adapt to much less obvious, nonlinear relationships present in data and learn them during model training.
- *Adapting to new data:* As new information becomes available ML models can adapt and change their parameters to capture new trends in the data. ML models can maintain their relevance and predictive power over time, even as the data changes.
- *New insights and solutions:* ML models are capable of uncovering novel insights and devising solutions that might not occur to human experts. In contrast, traditional models often hinge on hypotheses or assumptions bound by the rigidity of predefined structures.
- *Ability to learn from large, complex data:* Optimization algorithms that handle high dimensional data search can determine ML model parameters that capture the most important aspects (signal) from big data. Deep NN models can handle diverse and unstructured data, such as video/image, point cloud, text, speech, and geospatial data.

Why use ML models? ML has already had a transformational impact on many industries, including banking and finance, customer service, healthcare, cybersecurity, and marketing. Recent advancements in deep learning methods have opened the door to many new applications. Some of the application areas that have been revolutionized by ML include chatbots, image processing, content generation, robotics, forecasting, and anomaly detection. These developments are why the *Harvard Business Review* referred to AI/ML as "the most important general-purpose technology of our era" (Brynjolfsson and McAfee 2017).

ML methods may be a good choice if the task requires recognition of patterns within data, automation of repetitive tasks, and the ability to adapt over time. However, these methods often require access to a large quantity of relevant, quality data. They also typically suffer from a lack of explainability (the "black-box" problem). Finally, they may require significant resources in terms of computing and data infrastructure.

According to a survey of state Departments of Transportation (DOT) conducted as part of this research project (Ch. 2 in Cetin et al. 2024), the following transportation application areas are those with the most developed, implemented, or procured ML solutions. Application areas are listed below in descending order starting with the most common (percentages indicate how many of the respondents selected the corresponding option).

1. Asset management and maintenance (25.6%)
2. Transportation systems management and operations (16.3%)
3. Intersection or road safety improvement (9.3%)
4. Construction, rehabilitation, materials (7.0%)
5. Commercial vehicle and freight operations (4.7%)
6. Transportation planning demand forecasting, land use (2.3%)
7. Other (16.3%)

Over 75% of survey respondents answered that they were somewhat or very satisfied with their agency's ML solution. Figure 3 outlines the types of value that ML solutions can provide and hypothetical examples from the transportation realm.

ML Value	Transportation Example
Respond to changing conditions	An ML adaptive signal control system can improve traffic flows by responding to dynamic conditions.
Make faster and better decisions	An ML traffic monitoring and incident management system can identify highway collisions in real-time and recommend strategies for first responders.
Identify new strategies	An ML system that supports transportation planning can craft a novel solution that would not have been previously considered by planners.
Maximize limited staff resources	ML can streamline agency operations through automation of repetitive tasks, such as permit processing, by extracting relevant information from applications, assessing them against predefined criteria, and even recommending approval or denial.
Encode agency expertise	ML can capture knowledge of highly trained maintenance personnel to detect and diagnose structural failings of equipment. Encoding agency expertise could become increasingly valuable amidst retirements.

FIGURE 3. EXAMPLE ML VALUE IN TRANSPORTATION

State of Practice: *What are State DOTs doing with ML?*

Despite ML's many potential operational and system benefits, it is not widely used in state and local transportation agencies today. Most agencies (~59%) indicated in the summer 2022 survey as part of this research effort (Ch. 2 in Cetin et al. 2024) that their agency does not have any ML applications currently deployed or being developed. Additionally, most agencies (~68%) indicated in the same survey that their agency is "not very" or "not at all" familiar with ML methods and tools. Some insights on the state of the practice with respect to those agencies that *are* pursuing ML are summarized below:

Common Transportation Areas for ML: Operations and asset management appear to be the most popular areas for ML at agencies today, but the applications vary. There also appears to be a lot of research emphasis on safety-related applications, such as hazard detection and driver behavior monitoring. Figure 4 illustrates ML examples from California, Delaware, and Missouri (Ch. 3 in Cetin et al. 2024) as well as from Texas (Granger and McCulloch 2024), Washington (NOCoE 2021), and Nevada (Maynard 2020).

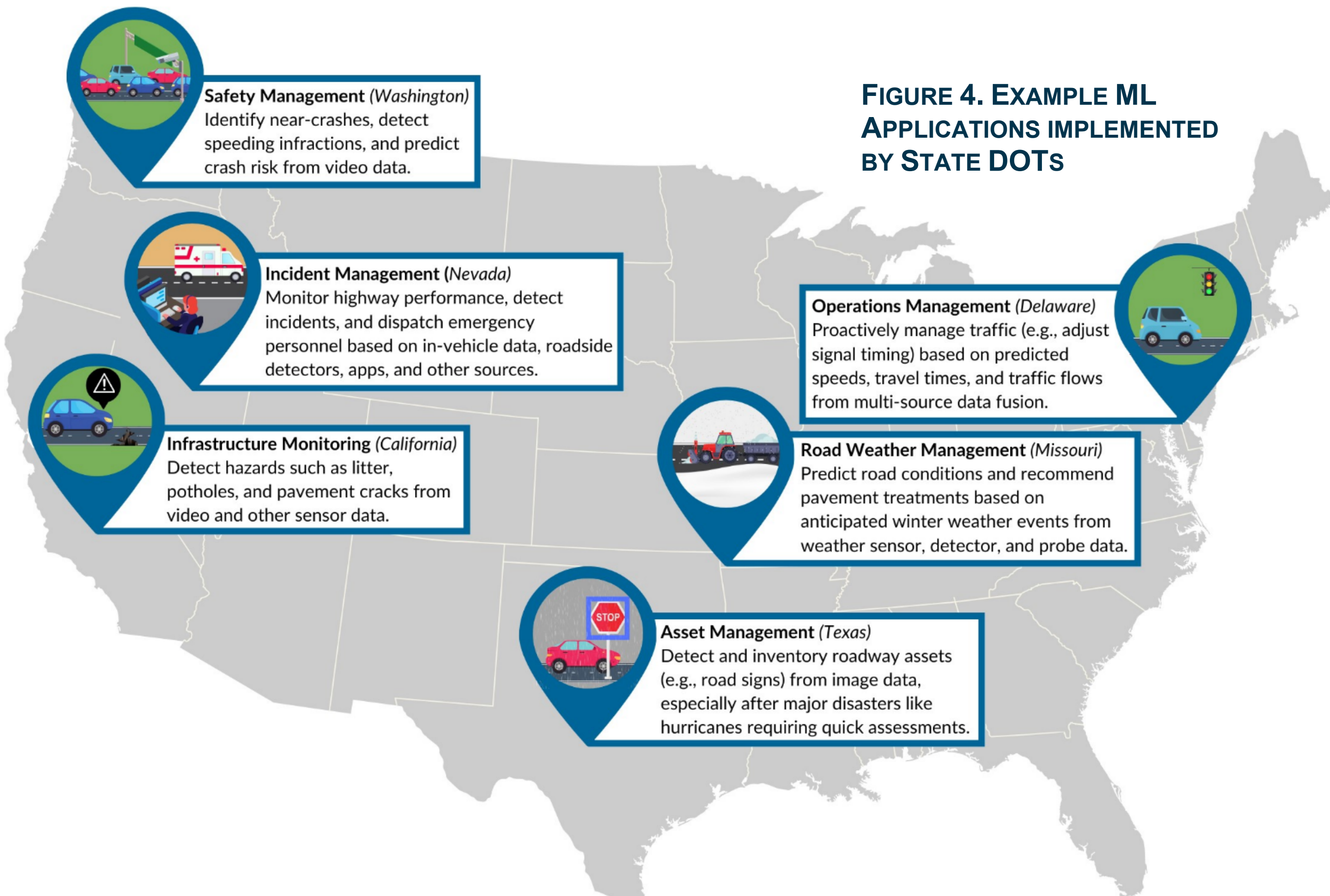

FIGURE 4. EXAMPLE ML APPLICATIONS IMPLEMENTED BY STATE DOTS

Common Types of ML: Supervised ML (i.e., learning from labeled data) with a human-in-the-loop seems to be the most prevalent form of ML being developed or implemented at agencies. Some popular areas include computer vision (usually with deep learning) for detection and classification tasks and various ML methods for short-term prediction tasks. Additionally, edge computing is becoming increasingly common, especially as more vendors are offering their "all-in-one" sensing, computing, and detection devices.

Procurement/Collaboration: DOTs typically lack in-house expertise in ML. Of the agencies developing or implementing ML, most seem to procure ML capabilities from consultants/vendors and/or leverage their university partners. However, investing in internal capabilities can help deployment success.

ML Development: Few ML developers, whether they be within the agency or from a consultant, vendor, or university partner, are developing new ML solutions from scratch. Instead, developers commonly use available pre-trained baseline models (e.g., YOLO for object detection) and other open-source tools as a starting point.

Data: Agencies are using a variety of data sources to support their ML applications. Many appear to be using their existing agency data sources when possible (e.g., CCTV cameras, weather sensors, detectors) as well as acquiring or purchasing additional data sources (e.g., INRIX, Waze).

Supporting Technology: Data storage, computational, and software resources are becoming increasingly important foundational elements to support ML applications. These elements are commonly sold as a subscription service. ML as-a-service is becoming more common as well, especially following a recent boom in generative AI tools, such as ChatGPT, which was released in late 2022. While procuring software on a subscription basis was considered an emerging practice for most DOTs five years ago (Gettman 2019), today it is increasingly common practice. The agency's role in digital infrastructure has evolved from infrastructure builder/operator/maintainer to infrastructure service manager today, bringing a greater need to communicate with diverse digital services and platforms (Gopalakrishna 2023).

Costs and Funding: Pricing models vary based on computing cycles, data storage size, the frequency of analytics, the level of customization, and other metrics, making it difficult to estimate how much an application will cost (Gettman 2019). ML project costs can vary widely depending on the availability of supporting data and resources, the nature of the task, and the scope, schedule, and scale of the deployment. In speaking with various State DOTs about their ML pilots, project budgets ranged widely from $25,000 to over $10 million (Ch. 3 in Cetin et al. 2024). Some agencies are using federal grant funding to kickstart their ML programs. For example, grants from U.S.DOT's Advanced Transportation and Congestion Management Deployment (ATCMTD) Program (now called Advanced Transportation Technology and Innovation, ATTAIN) have helped support various ML-focused deployments, including those with Delaware and Missouri DOTs. Strengthening Mobility and Revolutionizing Transportation (SMART) grants could be another potential option.

Best Practices: *How to implement ML successfully?*

While ML's future looks bright and expansive, it is not suitable for all problems and sometimes brings new challenges and risks. Agencies need to be aware of ML's potential benefits as well as its challenges, limitations, and risks to make informed decisions about how it is deployed within the agency and across the transportation network. To help state DOTs and other transportation agencies kickstart (or expand) their journey into the rapidly evolving world of ML, the research team developed a 10-step roadmap to building agency ML capabilities (Figure). The roadmap attempts to be sufficiently specific to ML at state DOTs while remaining method-agnostic and adaptable to the changing ML landscape.

The roadmap is included as part of a broader ML guide. Insights in the guide are based heavily on best practices and lessons learned synthesized over the past two years from a variety of tasks, including a literature review, a survey of agencies that received 43 responses, and five case studies based on interviews with state DOT teams developing and/or deploying ML in different capacities. The top guide takeaways are summarized below. Please see the complete "Guide on Implementing and Leveraging Machine Learning at State Departments of Transportation" for more information.

ML GUIDE KEY TAKEAWAYS

EXPECTATIONS: ML is not a panacea and will not work for every transportation use case; however, it is becoming increasingly powerful and widespread. Agencies should understand which transportation problems are currently conducive to ML solutions.

DATA: ML is a bottom-up, data-driven approach capable of discovering highly complex patterns in data, whereas traditional approaches tend to be rule-based.

BENEFITS: ML can bring many benefits, such as improving operational efficiency (e.g., by replacing manual processing of large data) and generating new strategies by discovering hidden opportunities.

GAPS: ML may have different needs than traditional approaches, particularly with respect to digital infrastructure (e.g., computing, big data, storage, etc.).

APPLICATIONS AREAS: Many agencies have found success deploying ML in various application areas, such as operations and asset management.

RISKS: ML project implementations and ML solutions in operation introduce new challenges and risks to agencies such as their black-box nature; these risks should be well understood and managed.

APPROACHES: There are a variety of approaches an agency can take in deploying ML (e.g., custom in-house model development, purchasing ML as a service), with each approach having different benefits and risks.

EVALUATION: Agencies looking to deploy ML solutions should understand typical evaluation metrics for ML applications (e.g., false negative rate), what metrics are desirable to measure for their project, and how these metrics tie into the performance of the transportation system.

SCALING: As with other emerging technology deployments, it is considered a best practice with ML to start small, show value, and then scale up.

COSTS: Data processing and transmission costs could play a significant role in overall ML costs.

WORKFORCE: While agency staff do not have to be ML experts, it is important for them to understand whether and how ML is used by vendors/consultants and be cognizant of potential pitfalls in deployment (e.g., model drift).

ROADMAP TO BUILDING AGENCY MACHINE LEARNING CAPABILITIES

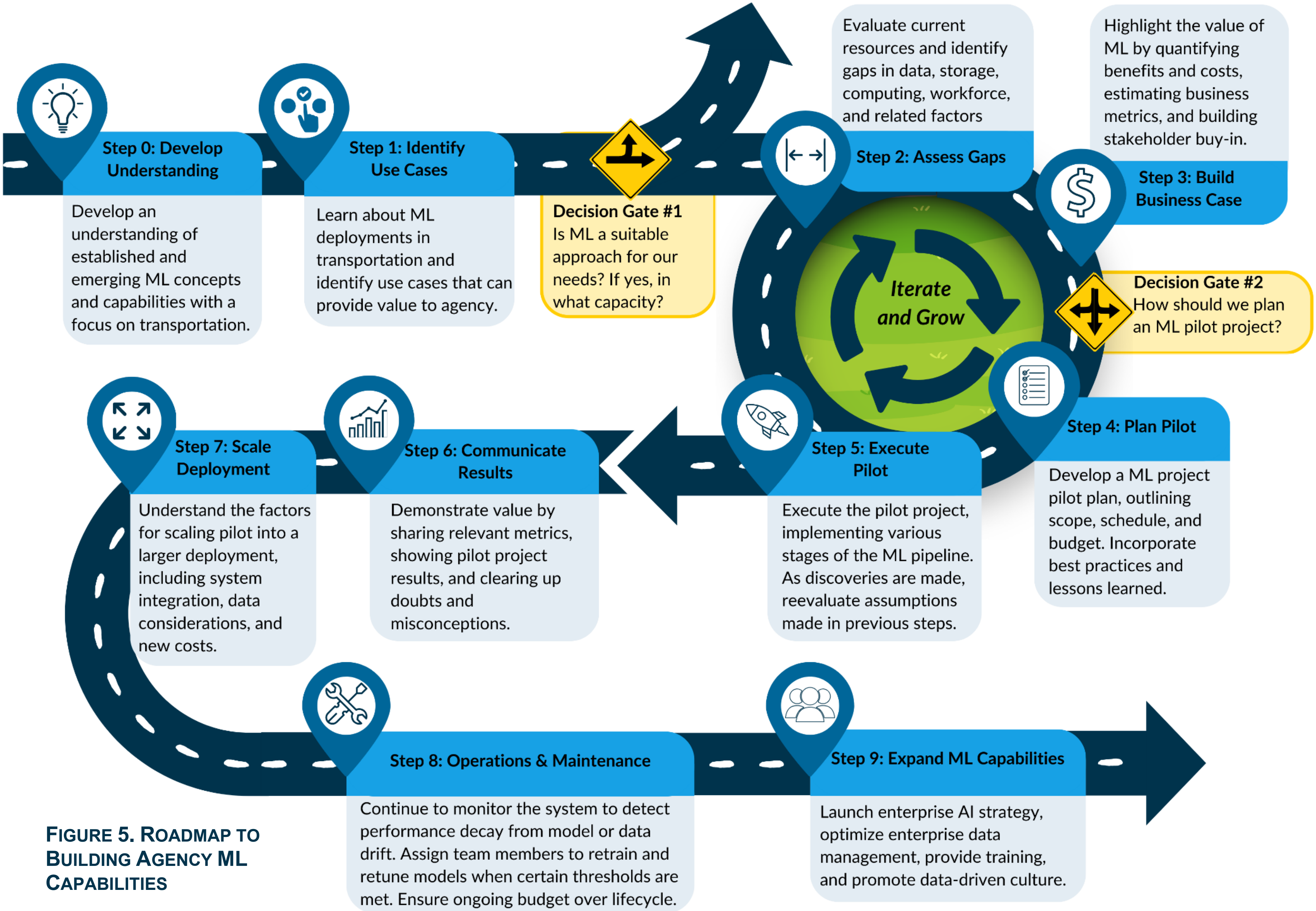

FIGURE 5. ROADMAP TO BUILDING AGENCY ML CAPABILITIES

Outlook: *What's next for ML in transportation?*

The ML landscape is evolving rapidly, driven by advancements in algorithms, computational power, and the availability of large datasets. Growing research on ML in transportation—as evidenced by the stark increase in the number and percentage of ML-related papers published in the Transportation Research Record (TRR) since 2017—serves as a harbinger of ML implementation at transportation agencies. **Deep learning** in particular is growing in popularity, with over 30% of 2022 survey respondents indicating they have used or are developing deep learning applications (Ch. 2 in Cetin et al. 2024).

Even more recently, generative AI models, such as large language models (**LLMs**), have gained significant attention and made it possible to perform a wide variety of tasks without the need for coding expertise. ChatGPT, the generative AI-powered chatbot powered by an LLM that launched in late 2022, is among the most widely known. **ChatGPT** can write a stakeholder engagement plan, design an experiment, suggest ideas for a proposal, etc. Some agencies are beginning to explore the possibilities of LLMs to support their business functions. The Massachusetts DOT in collaboration with the University of Massachusetts is training a custom LLM to generate workforce development content based on their contracting documents and design guidelines (Newberry 2024). The callout box at right (Figure) shows the response from ChatGPT to a question on the top three strengths and weaknesses of ML.

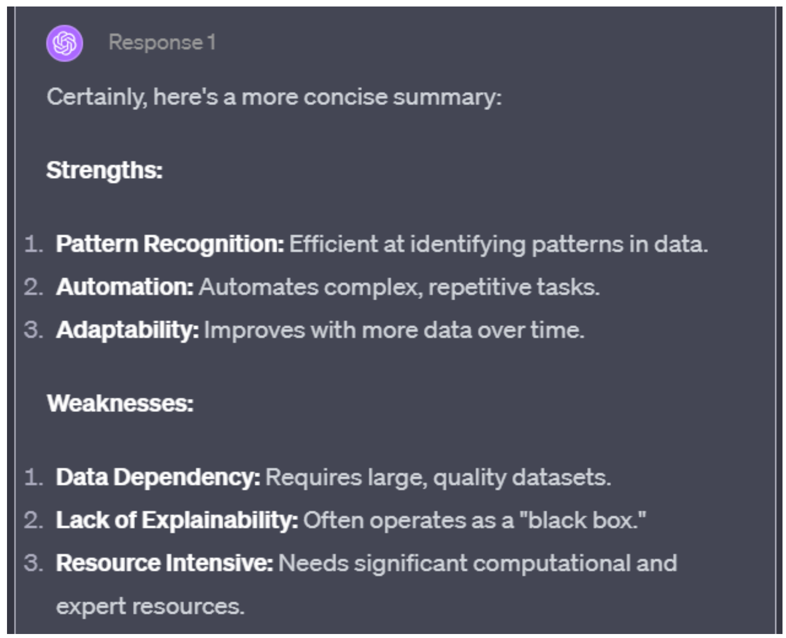

FIGURE 6. CHATGPT'S RESPONSE TO THE QUESTION OF ML'S TOP THREE STRENGTHS AND WEAKNESSES

These publicly available **generative AI** models operate with billions of parameters and are trained on vast amounts of data (think the entirety of the Internet). They are becoming increasingly powerful and capable, generating not only text but also images, videos, audio, and code. Despite their impressive capabilities, they have some important drawbacks, some of which are summarized here:

- **Ethical concerns:** Ownership of the created content and compliance with copyright laws are growing concerns since generative AI models are trained on creators' work without their clear permission.
- **Incorrect or misleading responses:** These models are not error-proof and can still generate inaccurate or misleading responses ("hallucinations") that *appear* logical and credible.
- **Lack of explainability:** These models are tremendously complex and opaque. Tools like ChatGPT are not able to summarize specific references supporting their responses.

- **Lack of transportation expertise:** Generative AI tools like ChatGPT are generalized models, and therefore, are not able to produce highly specific results in a transportation context without additional background information or fine-tuning (i.e., adapting the pre-existing LLM to a more specific task or domain), and even that is likely to be insufficient.

As the ML landscape evolves, ML implementation processes in transportation evolve as well. For example, the level of effort needed for model training may diminish in the future as more robust multipurpose pre-trained models, such as LLMs, become widely used. Overall, most ML-related advancements are expected to occur outside of the DOT via product developers, car companies, consultants, etc. It is important for the DOT to have a workforce that can monitor and manage these developments as they begin to impact the field of transportation generally and the agency specifically. Some important trends that will likely impact how ML solutions are procured and deployed by transportation agencies in the future are listed below.

ML Trends Impacting Transportation Agencies

AutoML and MLaaS: Automated machine learning (AutoML) and machine learning as a Service (MLaaS) offerings are making ML more accessible to non-experts. These are expected to increase the usage of ML since the need for expertise and a skilled workforce will be minimized.

Algorithmic Innovations: New ML algorithms and architectures, particularly in deep learning, are being developed at a rapid rate. Innovations like attention mechanisms, transformers, and generative adversarial networks (GANs) have opened new possibilities in areas such as natural language processing and synthetic data generation. These innovations help create new models (e.g., LLMs) that can solve a broad range of problems.

Data Availability: ML models thrive on large datasets, and the increasing availability of big data has been a significant driver of ML progress. As more transportation data become available and more ML models are developed and tested, such models are expected to become more widely available and accessible to agencies.

Cloud Computing: Deploying ML models on cloud platforms allows access to necessary computational resources and alleviates the need to invest in expensive infrastructure.

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