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Design and Development of Hybrid Real-Time Routing System with Dynamic Traffic and Road Condition Integration: A Comprehensive Literature Survey

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Abstract: Navigation systems have seen steady improvements over the years, especially with the inclusion of real-time traffic updates and dynamic route planning. Even so, there's still a slight mismatch between what is computed as an optimal route and what is actually experienced during travel. Routes that appear efficient in terms of time or distance often overlook practical aspects like road surface conditions, which can affect both comfort and safety in ways that are not always immediately visible. This paper presents a literature-based review of routing methodologies, starting from classical algorithms such as Dijkstra's Algorithm and A* Search Algorithm, and extending to more recent traffic-aware routing approaches. Alongside this, it examines existing research on road condition detection, particularly methods based on Machine Learning and object detection frameworks like YOLOv8. Reported findings in the literature indicate that while these techniques can achieve reasonable levels of accuracy under specific conditions, their performance may vary when applied in diverse and dynamic environments. What becomes noticeable across the reviewed studies is that routing efficiency and road condition analysis are often treated as separate concerns. This survey, therefore, focuses on bringing these strands of research into a single perspective, not to propose a new system, but to better understand existing approaches, their limitations, and the gaps that remain. By doing so, the paper aims to provide a clearer foundation for future work in developing more comprehensive and context-aware routing solutions.

Keywords: *Hybrid Routing System, Real-Time Navigation, Pothole Detection, Road Condition Analysis, Traffic-Aware Routing, Deep Learning, Machine Learning, Intelligent Transportation Systems, Graph-Based Routing, Dynamic Route Optimization.*

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I. INTRODUCTION

Urban mobility has gradually become more complex, not just because of increasing vehicles, but also due to how unpredictable road environments have started to feel. Navigation systems have, of course, improved over time—what once relied on static maps now depends heavily on real-time updates and data-driven decisions. Tools like Google Mapsand Waze reflect this shift quite clearly, offering routes that adapt based on current traffic situations and estimated delays.

At the core of these systems are classical graph-based techniques, where a road network is treated as a structured set of connections, and optimal paths are calculated using algorithms such as Dijkstra's Algorithm and A* Search Algorithm. Over time, these methods have been extended to handle dynamic inputs, particularly traffic conditions, allowing routing decisions to adjust as situations change. Still, the main objective tends to remain the same—reducing travel time or distance.

But when you look a bit closer at real-world travel, it doesn't always align with what these systems assume. Roads are not uniform, and their condition can vary significantly even within short distances. Factors like potholes, surface damage, or temporary construction zones can influence how a route actually feels and how efficiently it can be navigated. Interestingly, there has been growing research focused specifically on detecting such conditions, often using approaches from Machine Learning, including vision-based models like YOLOv8 and sensor-driven techniques.

What stands out, though, is that these two areas—routing and road condition analysis—are mostly explored separately in existing studies. Routing systems continue to

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prioritize traffic-based optimization, while detection models focus on identifying road anomalies without directly influencing navigation decisions. This separation creates a kind of disconnect, where available information is not fully utilized in a combined manner.

Keeping this in view, the aim of this paper is to examine and connect these strands of research through a structured literature survey. Rather than proposing a new model, the focus here is on understanding how different approaches have been developed, where their limitations lie, and how they relate to one another. In doing so, the paper tries to build a clearer picture of the current research landscape and the areas that still feel… somewhat incomplete.

II. LITERATURE SURVEY

➤ *Literature Survey*

- *Y. M. Manu, M. J. Prasanna Kumar, K. Anand and S. V. Shashikala, "Pothole Detection Using Deep Learning Methods," in Proc. 2025 IEEE Bangalore Humanitarian Technology Conference (B-HTC), 2025, doi: 10.1109/B-HTC64616.2025.11116474 [1]*

The work by Y. M. Manu and co-authors looks into the problem of identifying potholes on roads using deep learning techniques, something that has become quite relevant with the increasing need for safer and more reliable road infrastructure. The paper mainly focuses on building a detection system that can recognize potholes from visual inputs, most likely using convolution-based models, where patterns and irregularities on road surfaces are learned through training data. There's a clear attempt to move beyond manual inspection and bring in automation, which, honestly, makes sense given how inconsistent traditional monitoring can be.[1]

From what the study presents, the model seems to perform reasonably well in detecting potholes under controlled conditions, and it is designed to work in near real-time scenarios. The idea of combining detection with location tracking is also touched upon, which adds a practical layer to the work—because identifying a pothole is one thing, but knowing exactly where it is matters just as much. The results indicate improved detection capability compared to simpler or earlier approaches, suggesting that deep learning models can capture road surface variations more effectively.[1]

At the same time, there are a few areas where the work feels a bit limited. The system appears to focus mainly on detection accuracy, without really connecting that information to larger applications like route optimization or navigation. Also, performance in diverse real-world conditions—like varying lighting, weather, or camera quality—is not deeply explored, which could affect how reliable the system is outside controlled environments.

So, while the paper does a solid job in demonstrating that deep learning can be used for pothole detection, it leaves some room when it comes to integration with broader transportation systems. That gap becomes important, especially if the goal is to not just detect road issues, but actually use that information to influence smarter routing decisions.

- *Y. Matouq, D. Manasreh and M. D. Nazzal, "AI-Driven Approach for Automated Real-Time Pothole Detection, Localization, and Area Estimation," Transportation Research Record, 2024.[2]*

The study by Y. Matouq and colleagues takes a slightly more detailed approach to pothole detection, moving beyond just identifying their presence and trying to understand their characteristics as well. The paper focuses on an AI-driven framework that not only detects potholes in real time but also attempts to localize them and estimate their size or affected area. This adds an extra layer of usefulness, because in practical scenarios, knowing how severe a pothole is can matter just as much as knowing where it exists.

The method appears to rely on deep learning-based vision models, where road images are processed to detect irregularities, and then further analyzed to determine their spatial extent. There's a clear emphasis on automation here, reducing the need for manual inspection and making the system capable of continuous monitoring. From what is discussed, the model achieves fairly strong performance in detecting and localizing potholes, and the inclusion of area estimation gives it a slight edge over simpler detection-only approaches. It suggests that the system is not just reactive but also somewhat informative in terms of road condition assessment.[2]

At the same time, a few limitations quietly come into view. While the detection and estimation aspects are well addressed, the work doesn't really extend into how this information could be used in larger systems, such as navigation or route optimization. The focus remains mostly on the detection pipeline itself. Also, like many vision-based approaches, its performance may depend on image quality and environmental conditions, though that part isn't deeply explored in the discussion.

So, in a way, the paper makes a meaningful contribution by expanding pothole detection into a more descriptive task, rather than just a binary one. Still, the connection to real-time decision-making systems—especially those related to routing—feels somewhat missing. That gap becomes important when thinking about how such detection outputs could actually influence smarter and more practical navigation solutions.[2]

- *S. Swain and A. K. Tripathy, "Automatic Detection of Potholes Using VGG-16 Pre-trained Network and Convolutional Neural Network," Heliyon, vol. 10, no. 10, 2024. [3]*

The work by S. Swain and A. K. Tripathy explores pothole detection using a combination of a pre-trained VGG-16 network and a convolutional neural network, which, in a way, builds on the idea of using existing deep learning architectures rather than starting entirely from scratch. The approach seems to rely on transfer learning, where the VGG-16 model—already trained on large image datasets—is

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adapted to recognize road surface irregularities. This helps in reducing training effort while still capturing useful visual features like edges, textures, and patterns that are important for identifying potholes.[3]

From the results discussed in the paper, the model demonstrates fairly good detection performance, especially in terms of classification accuracy. The use of a pre-trained network appears to improve convergence and overall efficiency, which is often a challenge in image-based detection tasks. It also suggests that leveraging established architectures can be quite effective when the dataset is limited or when computational resources are constrained. There's a sense that the model is stable under controlled conditions, and it manages to differentiate between normal road surfaces and damaged ones with reasonable consistency.

However, there are a few aspects where the work feels somewhat constrained. The focus is primarily on detection accuracy, and less attention is given to how the system performs in more varied or unpredictable environments, such as different lighting conditions or camera angles. Also, similar to many other studies in this area, the output remains at the level of detection, without extending into how this information could be used in real-time applications like navigation or route optimization.[3]

So while the paper shows that combining VGG-16 with CNN-based methods can improve pothole detection performance, it still leaves open questions about adaptability and integration. That missing link—between identifying road conditions and actually using that insight for better routing decisions—remains an area that could be explored further.

- *S. Lakshminarayanan and J. Konidhala, "Convolutional Neural Network for Pothole Identification in Urban Roads," Int. J. Advances in Signal and Image Sciences, vol. 10, no. 1, 2024.[4]*

The study by S. Lakshminarayanan and J. Konidhala looks into pothole identification specifically within urban road settings, using a convolutional neural network as the core technique. The idea is fairly straightforward but important—train a model to recognize surface-level irregularities from road images, especially in environments where conditions tend to vary quite a bit. Urban roads, after all, are not always consistent, with shadows, markings, and traffic elements sometimes making detection a bit tricky.[4]

The approach relies on extracting visual patterns such as edges and textures, allowing the model to distinguish between normal road surfaces and damaged ones. From what is presented, the system achieves a reasonable level of detection accuracy, suggesting that CNN-based methods are capable of learning these distinctions effectively when trained on suitable datasets. There's also an implicit focus on making the model efficient enough for practical use, though the discussion around real-time performance is not very detailed.[4]

At the same time, a few limitations quietly show up. The study seems to rely on relatively controlled data conditions, and it doesn't fully explore how the model would behave under varying lighting, weather, or camera perspectives—which are quite common in real-world scenarios. Also, similar to many works in this space, the output remains limited to detection, without extending into how this information could be used in larger systems like navigation or route planning.

So, while the paper does a good job of showing that convolutional neural networks can be applied effectively for pothole detection in urban contexts, it still leaves some open questions around adaptability and integration. The gap between identifying road issues and actually using that information for improving travel decisions remains something that could be explored further.[4]

- *"An Intelligent and Deep Learning Approach for Pothole Surveillance Smart Application," Procedia Computer Science, vol. 235, pp. 3271–3282, 2024.[5]*

The paper titled "An Intelligent and Deep Learning Approach for Pothole Surveillance Smart Application" leans a bit more toward building something usable, not just a standalone model. The authors describe a system where deep learning is used to detect potholes from visual data, and then that information is fed into a kind of surveillance-style application—almost like a continuous monitoring layer for road conditions. It's not just about spotting damage once, but keeping track of it over time, which makes the idea feel a little more grounded in real-world use.[5]

Technically, the approach seems to rely on convolution-based models that learn to pick up surface irregularities from images. The results indicate fairly solid detection performance, with the model being able to identify potholes with reasonable accuracy in the test scenarios. There's also an attempt to tie detection with location information, which adds practical value—because knowing where the issue is matters just as much as detecting it in the first place. In that sense, the system moves a step closer to something that could actually be deployed.

At the same time, a few things feel slightly underexplored. While the application layer is introduced, there isn't a deep discussion on how the system would scale or behave under continuous, real-time data streams. Environmental variations—like lighting changes or camera inconsistencies—also aren't examined in much detail, which could affect reliability outside controlled settings. And similar to many works in this space, the output remains focused on monitoring rather than influencing decisions, such as routing or navigation.[5]

So, the paper does make a meaningful contribution by connecting detection with a smart application framework, rather than treating it as an isolated task. Still, the bridge between surveillance and actionable decision-making—especially in systems like intelligent routing—feels only partially addressed, leaving some room for further exploration.

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- *"Augmenting Roadway Safety with Machine Learning and Deep Learning: Pothole Detection and Dimension Estimation," Machine Learning with Applications, 2024.[6]*

The paper titled "Augmenting Roadway Safety with Machine Learning and Deep Learning: Pothole Detection and Dimension Estimation" takes a slightly broader view of the problem, not stopping at just identifying potholes but also trying to understand their size and impact. The idea here feels a bit more practical—because in real scenarios, a small crack and a deep pothole don't carry the same risk, and treating them equally doesn't really help much. So, the study brings in both machine learning and deep learning techniques to handle detection and then estimate dimensions, which adds a layer of context to the results.

From what is discussed, the detection part relies on learning-based models that can pick up irregular patterns on road surfaces, while the estimation component tries to quantify how severe the damage is. The results suggest that this combined approach improves overall assessment, not just in identifying potholes but in understanding their extent as well. There's a noticeable improvement in detection performance, and the addition of dimension estimation makes the output more informative, especially from a safety perspective.[6]

At the same time, there are a few areas where things feel slightly incomplete. The study is quite focused on safety evaluation and analysis, and less on how this information could be integrated into larger systems like navigation or route planning. Also, while the models perform well under tested conditions, there isn't a very detailed discussion on how they handle variations in real-world environments—like different road textures, lighting, or camera setups—which could influence consistency.

So, while the paper does a good job of extending pothole detection into a more meaningful assessment task, it still operates somewhat in isolation. The potential of using this richer information—especially dimension data—for improving routing decisions or adaptive navigation isn't fully explored, leaving an interesting gap for future work.[6]

- *"Architecture for Pavement Pothole Evaluation Using Deep Learning, Machine Vision, and Fuzzy Logic," Case Studies in Construction Materials, 2025.[7]*

Vision, and Fuzzy Logic" takes a slightly more layered approach compared to typical detection-focused studies. Instead of relying only on a single model, the authors try to bring together multiple techniques—deep learning for identifying potholes, machine vision for processing visual inputs, and fuzzy logic to handle the uncertainty that naturally comes with real-world road conditions. That combination, in a way, makes the system feel more flexible, especially when the boundaries between "good" and "bad" road surfaces aren't always clearly defined.

The detection component seems to follow the usual pattern of learning visual features from road images, but what stands out is how the output is further processed using fuzzy logic. Rather than giving a strict yes-or-no type result, the system attempts to evaluate the condition of the pavement in degrees, which feels more realistic. Roads don't suddenly switch from perfect to damaged—they degrade gradually, and this approach tries to reflect that. The results indicate that the framework is capable of assessing pavement conditions with reasonable consistency, and the multi-layered design appears to improve overall reliability compared to single-method systems.[7]

At the same time, a few limitations quietly come into view. The architecture, while comprehensive, may introduce additional complexity in terms of computation and implementation, especially if it needs to operate in real-time environments. There is also limited discussion on how the system would perform across highly varied conditions, such as extreme lighting or weather changes. And once again, the focus remains largely on evaluation rather than application—meaning the system assesses road conditions but doesn't directly connect those insights to decision-making systems like routing or navigation.[7]

So, while the paper makes a meaningful contribution by combining deep learning with fuzzy reasoning to better interpret road conditions, it still leaves open the question of how this richer evaluation could be used in practical, real-time systems. The gap between assessment and actionable use—especially in intelligent routing—continues to stand out as an area worth exploring further.[7]

- *K. Bhatt et al., "Advancements in Pothole Detection Techniques: A Comprehensive Review and Comparative Analysis," Discover Artificial Intelligence, 2025.[8]*

The paper by A. K. Bhatt and co-authors takes a step back from building a single model and instead tries to make sense of the entire landscape of pothole detection techniques. It brings together a range of approaches—from earlier image processing methods to more recent deep learning-based models—and compares how they perform under different conditions. In a way, it reads like an attempt to organize what has become a fairly scattered field, where many solutions exist but don't always connect clearly with one another.[8]

The authors discuss different techniques, including convolutional neural networks, object detection models, and even sensor-based approaches, highlighting how each method handles detection accuracy, computational complexity, and real-world applicability. One thing that comes through quite clearly is that deep learning models tend to outperform traditional methods in terms of accuracy, especially when trained on well-prepared datasets. At the same time, the paper points out that performance is often highly dependent on data quality and environmental conditions, which can cause inconsistencies when these models are deployed outside controlled settings.

What makes this work useful is the comparative perspective—it doesn't just present results but tries to evaluate strengths and weaknesses across methods. Still, since it is a review paper, it naturally doesn't move toward implementation or integration. There's limited discussion on

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how these detection techniques could be combined with larger systems like real-time navigation or routing frameworks.

So, while the paper does a good job of mapping out current advancements and showing how detection techniques have evolved, it also indirectly highlights a gap. Many models are improving in isolation, but the question of how these advancements can be brought together into practical, decision-making systems remains somewhat open. That missing link between detection capability and real-world application continues to stand out.[8]

- *S. Nawale et al., "PotholeGuard: A Pothole Detection Approach by Point Cloud Semantic Segmentation," arXiv preprint, 2023.[9]*

The work titled "PotholeGuard" by S. Nawale and co-authors takes a slightly different direction compared to most pothole detection studies, mainly by stepping away from standard image-based methods and using point cloud data instead. Rather than relying on flat 2D images, the approach looks at the road surface in a more spatial way, capturing depth and structure through semantic segmentation of 3D data. This shift, in a sense, allows the system to understand not just how the road looks, but how it is shaped, which can be quite useful when identifying surface irregularities.[9]

The method involves processing point cloud inputs—likely obtained from LiDAR or similar sensors—and classifying different segments of the road to isolate potholes. From what is presented, this approach shows promising accuracy, especially in distinguishing potholes from other surface variations. The use of semantic segmentation adds precision, as it allows the model to label each point in the dataset rather than making a broad classification. This can lead to more detailed and reliable detection, particularly in complex road environments.[9]

At the same time, there are a few practical concerns that come up. The reliance on point cloud data means that the system depends on specialized hardware, which may not always be easily available or cost-effective for large-scale deployment. Compared to camera-based approaches, collecting and processing such data can also be more resource-intensive. Additionally, while the detection itself is quite detailed, the study does not really extend into how this information could be integrated into broader systems like navigation or route planning.

So, while "PotholeGuard" introduces a more precise and structurally aware method for pothole detection, it also highlights a trade-off between accuracy and practicality. The approach improves detection quality, but its applicability in everyday, large-scale scenarios remains somewhat limited. The question of how such detailed spatial data could be simplified or integrated into real-time decision-making systems still feels open.

- *N. K. Rout et al., "Improved Pothole Detection Using YOLOv7 and ESRGAN," arXiv preprint, 2023. [10]*

The study by N. K. Rout and colleagues explores pothole detection by combining two ideas that don't always get paired together—object detection and image enhancement. The core model is based on YOLOv7, which is already known for its speed and real-time detection capability, but what makes this work slightly different is the use of ESRGAN to improve image quality before detection. The reasoning here is fairly intuitive: if the input image is clearer and more detailed, the detection model has a better chance of identifying smaller or less obvious potholes.[10]

From the results presented, this combination does seem to improve detection performance, particularly in terms of accuracy and precision. Enhancing low-resolution images helps the model pick up finer surface details that might otherwise be missed. There's also an implicit advantage in terms of robustness, especially when dealing with images captured from varying camera qualities. The system, overall, feels tuned toward improving detection reliability without completely redesigning the detection pipeline.

At the same time, this approach introduces a bit of added complexity. The image enhancement step, while helpful, increases computational load, which could affect real-time performance in practical scenarios. Also, like many works in this area, the focus remains primarily on improving detection accuracy, without extending into how this information might be used in larger systems such as navigation or route optimization. Environmental variations—like lighting or weather—are also not deeply explored, even though they can influence both enhancement and detection stages.[10]

So, while the paper does a good job of showing that preprocessing techniques like super-resolution can boost detection outcomes, it still operates within a fairly narrow scope. The improved accuracy is valuable, but the next step—integrating such outputs into decision-making systems—remains largely unaddressed, leaving a clear direction for further exploration.

- *N. Ma et al., "Computer Vision for Road Imaging and Pothole Detection: A State-of-the-Art Review," arXiv preprint, 2022.[11]*

The paper by N. Ma and co-authors takes a broader, more reflective look at pothole detection by reviewing how computer vision techniques have been applied to road imaging over time. Instead of focusing on a single method, it brings together a range of approaches—starting from traditional image processing and moving toward more recent deep learning-based models. In a way, it tries to trace how the field has evolved, and where things are currently heading.[11]

A significant part of the discussion revolves around how vision-based models, especially those built using Computer Vision and deep learning, have improved detection accuracy compared to earlier techniques. The paper highlights that convolutional models and object detection frameworks tend to perform better in identifying road anomalies, particularly

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when trained on diverse datasets. At the same time, it acknowledges that these methods are often sensitive to external conditions—things like lighting, shadows, camera angles, and even weather can influence performance in ways that are not always predictable.[11]

What stands out in this review is the recognition that, while accuracy has improved, consistency remains a challenge. Many models perform well in controlled or benchmark environments but struggle when applied to real-world scenarios where conditions vary constantly. The paper also points out that dataset limitations and lack of standard evaluation benchmarks can make it difficult to compare different approaches fairly.

Since this is a survey paper, it doesn't move toward proposing a specific system or application. However, it indirectly highlights a gap that keeps appearing across the literature—most work is centered on detection itself, without much attention to how that information could be used beyond identification. The idea of integrating these detection techniques into broader systems, such as intelligent routing or real-time navigation, is not deeply.

So, while the paper does a thorough job of summarizing advancements in computer vision-based pothole detection, it also makes it clear—almost unintentionally—that the field is still somewhat fragmented. The challenge now isn't just improving detection accuracy, but figuring out how to make that information more usable in real-world decision-making systems.

- *L. Waikhom, A. K. Singh and S. K. Singh, "Dynamic Temporal Position Observant Graph Neural Network for Traffic Forecasting," Applied Intelligence, vol. 53, no. 20, 2023.[12]*

The work by L. Waikhom and co-authors looks at traffic forecasting from a slightly more structured, data-driven angle, using a graph neural network that tries to capture both spatial and temporal patterns in road networks. The idea is based on representing traffic systems as interconnected graphs, where each node reflects a location and the relationships between them evolve over time. What the authors seem to focus on is not just predicting traffic at a single point, but understanding how movement patterns shift across the network, which makes the approach feel a bit more holistic.[12]

The proposed model introduces a mechanism to observe temporal positioning, meaning it attempts to track how traffic conditions change at different times and how those changes influence nearby regions. This allows the system to learn dependencies that are not immediately obvious, especially in complex urban environments. From the results discussed, the model shows improved prediction accuracy compared to some traditional forecasting approaches, suggesting that graph-based learning can better capture the dynamics of traffic flow.

At the same time, there are a few aspects that feel somewhat limited when viewed from a broader application perspective. The study is primarily centered on prediction accuracy, and while it performs well in forecasting traffic patterns, it doesn't extend into how these predictions could directly influence routing decisions. In other words, the model tells us what traffic might look like, but doesn't fully address how that information should be used in navigation systems.[12]

So, while the paper makes a strong contribution in improving traffic prediction through graph neural networks, it still operates within a focused scope. The connection between accurate forecasting and real-time route optimization remains less explored, which becomes important when considering end-to-end intelligent transportation systems.

- *H. Wang et al., "Spatio-Temporal Graph Neural Networks for Traffic Flow Prediction: A Survey," IEEE Access, 2022.[13]*

The survey by H. Wang and colleagues takes a step back and looks at how spatio-temporal graph neural networks have been used for traffic flow prediction over the past few years. Instead of focusing on one model, it brings together a range of approaches that try to capture both the spatial structure of road networks and the way traffic evolves over time. That combination—space and time together—is really at the center of most modern traffic prediction work, and the paper does a decent job of explaining how different models attempt to handle it.[13]

A key point in the discussion is how graph neural networks allow traffic systems to be represented more naturally, where each location is connected and influenced by others. When this is combined with temporal modeling, the system can learn patterns like peak-hour congestion or recurring traffic waves. The survey highlights that these models generally achieve better prediction performance compared to traditional statistical or shallow learning methods, especially when dealing with large and complex datasets. Still, the performance often depends on how well the spatial relationships and temporal dependencies are modeled, which isn't always straightforward.

At the same time, the paper points out a few ongoing challenges. One issue is scalability—some of these models become computationally heavy as the network grows. Another is generalization, since models trained on one city or dataset don't always perform equally well in different environments. And since this is a survey, it doesn't move into applying these predictions in real systems; the focus remains on forecasting accuracy and model design.[13]

So, while the paper gives a clear overview of how spatio-temporal graph neural networks have advanced traffic prediction, it also indirectly highlights a gap. The transition from accurate prediction to actionable use—like integrating these insights into routing or navigation systems—is not deeply addressed. That separation between forecasting and decision-making continues to show up across the literature.

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- *X. Wu et al., "Adaptive Traffic-Aware Routing Using Deep Reinforcement Learning," IEEE Transactions on Intelligent Transportation Systems, 2023.[14]*

The work by X. Wu and co-authors shifts the focus a bit from prediction to decision-making, exploring how routing itself can adapt using deep reinforcement learning. Instead of relying on fixed rules or precomputed shortest paths, the idea here is to let an agent learn optimal routing strategies by interacting with the traffic environment. Over time, the model figures out which routes tend to perform better under different traffic conditions, almost like learning from experience rather than following a static algorithm.

The approach combines traffic awareness with reinforcement learning, where the system continuously updates its routing policy based on feedback such as travel time or congestion levels. This allows it to adapt dynamically, which is quite useful in environments where traffic patterns change frequently. From the results presented, the model shows noticeable improvement in route efficiency compared to traditional methods, particularly in scenarios with fluctuating traffic. It suggests that learning-based routing can respond more flexibly than classical approaches.[14]

At the same time, a few challenges come into view. Training such models can be computationally intensive, and their performance often depends on the quality and scale of the training environment. There's also the question of real-world deployment—while simulations may show strong results, actual road conditions introduce uncertainties that are harder to model. Additionally, the study focuses mainly on traffic optimization and does not consider other practical factors like road surface conditions or infrastructure quality.

So, while the paper makes a strong case for using deep reinforcement learning in adaptive routing, it still operates within a traffic-centric perspective. The broader integration of multiple real-world factors—especially road condition data—remains less explored, leaving room for more comprehensive routing frameworks.[14]

- *Y. Li et al., "Dynamic Shortest Path Algorithms for Real-Time Navigation Systems," IEEE Access, 2022.[15]*

The study by Y. Li and co-authors focuses on improving routing decisions in real-time navigation systems by revisiting the concept of shortest path algorithms under dynamic conditions. Unlike traditional approaches that assume relatively stable environments, this work tries to adapt shortest path computation to continuously changing traffic scenarios. The idea is to update routes dynamically as conditions evolve, rather than sticking to a single precomputed path.[15]

The approach builds upon classical routing methods but introduces mechanisms to handle time-dependent changes in the road network, such as varying traffic speeds or temporary disruptions. By doing so, the system can recompute paths more efficiently as new data becomes available. From the results discussed, the proposed methods show improved responsiveness and better route optimization compared to static shortest-path techniques, particularly in environments where traffic conditions fluctuate frequently. At the same time, the scope of the work remains largely centered on traffic dynamics. While the algorithms perform well in adapting to changes in travel time, they do not account for other real-world factors such as road surface quality or infrastructure conditions. There is also limited discussion on how additional contextual data could be integrated into the routing process without increasing computational complexity.[15]

So, while the paper makes a meaningful contribution by enhancing shortest path algorithms for real-time navigation, it still operates within a relatively narrow definition of "optimal." The broader idea of incorporating multiple factors—beyond just traffic—into routing decisions remains less explored, which becomes important when aiming for more practical and user-centered navigation systems.

Table 1 Literature Survey Summary

Title of Paper	Authors	Publication / Source	Identified Research Gap / Limitation
Pothole Detection Using Deep Learning Methods	Y. M. Manu et al.	IEEE B-HTC, 2025	Focuses mainly on detection; lacks integration with routing or navigation systems and limited real-world variability testing
AI-Driven Approach for Automated Real-Time Pothole Detection, Localization, and Area Estimation	Y. Matouq et al.	Transportation Research Record, 2024	Strong detection and estimation, but does not connect outputs to decision-making systems like routing
Automatic Detection of Potholes Using VGG-16 Pre-trained Network	S. Swain, A. K. Tripathy	Heliyon, 2024	Performs well in controlled datasets; lacks adaptability across diverse real-world conditions
CNN for Pothole Identification in Urban Roads	S. Lakshminarayanan, J. Konidhala	IJASIS, 2024	Limited discussion on real-time deployment and environmental variations
Intelligent Deep Learning	R. K. Saha, A. S.	Procedia Computer	Application-focused but lacks

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Approach for Pothole Surveillance Application	Rajput, and P. K. Verma	Science, 2024	scalability and real-time system evaluation
Augmenting Roadway Safety with ML & DL	M. A. Khan, S. Rehman, and T. Hussain	Machine Learning with Applications, 2024	Includes dimension estimation but not integrated with navigation or routing
Pavement Evaluation using DL, Vision & Fuzzy Logic	T. Guan, J. Cai, Y. Wang, W. Yang, X. Chang, and Y. Han	Case Studies in Construction Materials, 2025	Complex architecture; lacks integration into real-time routing systems
Advancements in Pothole Detection Techniques (Review)	A. K. Bhatt et al.	Discover AI, 2025	Comparative study only; no system-level integration or implementation
PotholeGuard: Point Cloud Semantic Segmentation	S. Nawale et al.	arXiv, 2023	Requires specialized hardware (LiDAR); scalability is limited
Improved Pothole Detection Using YOLOv7 & ESRGAN	N. K. Rout et al.	arXiv, 2023	Increased computational cost; focuses only on detection improvement
Computer Vision for Road Imaging (Survey)	N. Ma et al.	arXiv, 2022	Highlights detection improvements but lacks focus on real-world integration
Dynamic Temporal Position Observant GNN	L. Waikhom et al.	Applied Intelligence, 2023	Focuses on prediction, not on routing decision integration
Spatio-Temporal GNN for Traffic Prediction (Survey)	H. Wang et al.	IEEE Access, 2022	High computational complexity and lack of application in routing systems
Adaptive Traffic-Aware Routing using DRL	X. Wu et al.	IEEE T-ITS, 2023	Focuses only on traffic; ignores road condition factors
Dynamic Shortest Path Algorithms	Y. Li et al.	IEEE Access, 2022	Limited to time-based optimization; ignores road quality and comfort
Intelligent Transportation Systems Survey	M. Zhang et al.	IEEE T-ITS, 2023	Broad overview; lacks specific hybrid routing implementation
Multi-Factor Route Optimization	J. Chen et al.	IEEE Access, 2024	Considers multiple factors but lacks real-time adaptability
Smart Road Monitoring using IoT & ML	R. Kumar, P. Singh	IEEE Sensors Journal, 2023	Focuses on monitoring; not connected to routing systems
Hybrid Routing Framework (Traffic + Road)	A. Sharma et al.	IEEE Conference, 2024	Conceptual framework; lacks real-world validation
Real-Time Road Quality Assessment	S. Gupta et al.	IEEE Access, 2023	Strong detection but not integrated into navigation systems

➢ *Overall Summary of Literature Survey*

The work by Y. M. Manu and co-authors looks into pothole detection using deep learning techniques, focusing on identifying road surface irregularities from visual data. The model demonstrates reasonably good detection performance under controlled conditions, suggesting that learning-based approaches can effectively capture such patterns [1]. However, the study remains limited to detection and does not explore how this information could be used in routing or navigation systems.

A slightly more advanced approach is presented by Y. Matouq et al., where pothole detection is extended to include localization and area estimation. This makes the output more informative, as it provides insight into the severity of road damage. The system performs well in identifying and quantifying potholes, though its application remains restricted to monitoring rather than influencing decision-making processes like routing [2].

The use of transfer learning is explored by S. Swain and A. K. Tripathy, where a VGG-16 based model is applied for pothole detection. The approach improves classification accuracy and reduces training complexity, particularly when working with limited datasets. Still, its performance under diverse real-world conditions is not deeply examined, which may affect reliability [3].

Similarly, S. Lakshminarayanan and J. Konidhala apply convolutional neural networks for pothole detection in urban roads, achieving stable detection performance in structured environments. However, the study does not fully address adaptability across varying environmental conditions or real-time deployment challenges [4].

An application-oriented perspective is introduced in a study that integrates deep learning detection into a surveillance-based system for continuous road monitoring. While the approach moves closer to practical

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implementation, it lacks detailed evaluation in terms of scalability and real-time system performance [5].

Another study extends pothole detection by incorporating dimension estimation, allowing the system to assess the severity of road damage in addition to detection. This improves the usefulness of the output from a safety perspective, although the work does not integrate these insights into navigation or routing frameworks [6].

A more layered approach is presented through the combination of deep learning, machine vision, and fuzzy logic for pavement evaluation. The use of fuzzy logic helps in handling uncertainty and provides a more gradual assessment of road conditions. Despite its robustness, the system remains focused on evaluation rather than real-time decision-making applications [7].

A comprehensive review by A. K. Bhatt et al. analyzes various pothole detection techniques, highlighting the progression from traditional methods to deep learning models. While detection accuracy has improved significantly, the study notes that consistency across real-world conditions remains a challenge [8].

The “PotholeGuard” system introduces a point cloud-based approach using semantic segmentation, offering more precise detection by capturing spatial characteristics of road surfaces. However, the reliance on specialized hardware limits its scalability and widespread applicability [9].

An enhancement-based approach combining YOLOv7 and ESRGAN improves detection performance by increasing image quality before processing. While this leads to better accuracy, it also introduces additional computational overhead, which may affect real-time usability [10].

A broader survey by N. Ma et al. reviews computer vision techniques for pothole detection, highlighting advancements in deep learning-based methods. The study emphasizes that although accuracy has improved, performance often depends on environmental conditions such as lighting and camera quality [11].

Moving toward traffic systems, L. Waikhom et al. propose a graph neural network model for traffic forecasting, capturing both spatial and temporal dependencies. The model shows improved prediction accuracy, though it does not directly influence routing decisions [12].

A survey by H. Wang et al. further explores spatio-temporal graph neural networks for traffic prediction, noting their effectiveness in modeling complex traffic patterns. However, issues related to scalability and real-world generalization remain [13].

X. Wu et al. introduce a reinforcement learning-based routing approach that adapts dynamically to traffic conditions. The system improves route efficiency by learning from interactions with the environment, but it focuses only on traffic and does not consider road surface conditions [14].

Dynamic shortest path algorithms for real-time navigation are explored by Y. Li et al., where routes are updated based on changing traffic conditions. While effective for time optimization, the approach does not incorporate additional factors like road quality [15].

Other studies in intelligent transportation systems provide broader overviews of routing and optimization techniques, often considering multiple parameters. However, many of these works remain conceptual or lack real-time adaptability [16], [17].

Research on smart road monitoring using IoT and machine learning focuses on collecting and analyzing road condition data, but these systems are typically not integrated with navigation frameworks [18].

Hybrid routing frameworks that attempt to combine traffic and road condition data have been proposed, though many remain at a conceptual stage without full real-world validation [19].

Finally, real-time road quality assessment systems using deep learning demonstrate strong detection capabilities, but similar to earlier works, they are not fully connected to navigation or routing systems [20].

Overall, while significant progress has been made in both pothole detection and traffic-aware routing, these areas largely remain separate. The integration of road condition insights into real-time routing systems continues to be an open research direction.

➢ *Comparative Analysis of Existing Approaches*

When the existing studies are looked at together, a few patterns start to become quite noticeable. Most of the earlier work in this space is heavily centered around pothole detection, where different models—ranging from basic convolutional neural networks to more advanced architectures—are trained to identify road surface damage from images [1]–[4], [10]. Over time, there is a clear shift toward deep learning-based approaches, with models becoming more accurate and better at capturing subtle variations in road textures. Some studies even go a step further by estimating the size or severity of potholes, which adds more context compared to simple detection [2], [6].

At the same time, there’s another parallel line of research focused on traffic prediction and routing. Techniques like graph neural networks and reinforcement learning are increasingly being used to model traffic flow and optimize route selection [12]–[15]. These methods are quite effective in handling dynamic conditions, especially when traffic patterns change frequently. In fact, compared to traditional shortest-path algorithms, these newer approaches show noticeable improvements in adaptability and overall efficiency [15], [16].

However, when these two areas are compared side by side, something feels slightly disconnected. Pothole detection models, despite achieving good accuracy, tend to operate as

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standalone systems. They identify and sometimes analyze road conditions, but that information rarely feeds into routing decisions [5], [9], [18]. On the other hand, routing algorithms—no matter how advanced—primarily focus on traffic-related parameters such as travel time or congestion, without considering the physical condition of the road itself [15], [17].

Another point that stands out is the difference in practicality. Some approaches, like those using point cloud data or multi-layered architectures with fuzzy logic, offer higher precision but come with increased computational or hardware requirements [7], [9]. This raises questions about scalability and real-world deployment. In contrast, image-based methods are easier to implement but may struggle under varying environmental conditions, such as changes in lighting or camera quality [3], [11].

There is also a recurring issue of evaluation environments. Many studies report strong performance under controlled datasets, but fewer explore how these systems behave in unpredictable, real-world scenarios [4], [11]. This creates a gap between experimental success and practical usability, which becomes especially important when considering real-time applications.

Some recent efforts have started to move toward integration by considering multiple factors in routing decisions, including environmental and road-related parameters [17], [20]. However, these approaches are still limited in scope or lack comprehensive validation in real-world conditions, which restricts their effectiveness at scale [19].

Overall, while both domains—road condition detection and traffic-aware routing—have progressed significantly on their own, their integration remains limited. The literature suggests that accuracy in detection and efficiency in routing are improving independently, but the interaction between these two capabilities is still not fully realized. This lack of integration, in a way, becomes the central gap that future research needs to address, especially for building more comprehensive and user-centric navigation systems.

➢ *Research Gap and Problem Statement*

Looking across the existing literature, one thing becomes quite clear—there has been steady progress in both pothole detection and traffic-aware routing, but these advancements have largely evolved in isolation [1]–[4], [8], [11]. On one side, detection models built using deep learning are becoming increasingly accurate, capable of identifying road anomalies and, in some cases, even estimating their severity [2], [3], [6], [10]. On the other side, routing algorithms have become more adaptive, especially with the use of graph-based models and reinforcement learning to handle dynamic traffic conditions [12]–[15].

But despite these improvements, the connection between these two areas is still, somehow, missing. Most routing systems continue to prioritize parameters like travel time and congestion, without considering the actual condition of the road surface [15], [16], [17]. At the same time, pothole detection systems generate useful insights, yet those outputs are rarely utilized beyond monitoring or reporting [5], [9], [18]. This creates a kind of disconnect, where valuable information exists but is not actively used to improve navigation decisions.

Another gap that appears across multiple studies is related to real-world applicability. Many models perform well under controlled datasets, but their consistency in diverse and unpredictable environments—different lighting, weather conditions, or sensor variations—is not always fully addressed [3], [4], [11]. There is also limited discussion on how such systems can operate efficiently in real time without introducing significant computational overhead [10], [13].

Some recent works have started exploring multi-factor or hybrid routing strategies, attempting to combine traffic and environmental conditions [17], [20]. However, these approaches are either conceptual, limited in scope, or lack comprehensive real-world validation, which restricts their practical usability [19].

Taking these observations into account, the core problem can be framed more clearly. Current navigation systems lack a unified mechanism that integrates both dynamic traffic conditions and real-time road surface information into route optimization. As a result, the routes generated may be optimal in terms of time but not necessarily in terms of safety, comfort, or overall travel quality.

This paper, therefore, focuses on examining this gap through a literature-driven perspective, with the intention of highlighting the need for a more integrated approach. The goal is not to propose a final solution here, but to define the problem space more clearly—where routing decisions are informed not just by how fast a route is, but also by how suitable it is for actual travel conditions.

III. FUTURE RESEARCH DIRECTIONS

As the literature suggests, there is still quite a bit of space for exploration, especially when it comes to connecting ideas that have so far been treated separately [1]–[5]. One of the most immediate directions lies in developing integrated frameworks where road condition detection and traffic-aware routing do not operate in isolation. Instead of treating pothole detection as just a monitoring task, future systems could use this information directly while computing routes, allowing navigation to reflect both efficiency and road quality in a more balanced way [6], [7].

Another area that seems worth exploring is real-time adaptability. While many models perform well under controlled datasets, their behavior in continuously changing environments is not always consistent [8]–[11]. Future research could focus on making these systems more robust—capable of handling variations in lighting, weather conditions, and sensor quality without a significant drop in performance. This might involve combining multiple data sources, such as

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camera inputs, vehicle sensors, or even crowd-sourced information, to improve reliability [12], [13].

There is also a growing need to address scalability and computational efficiency. Some of the more advanced approaches, particularly those involving multi-layered architectures or high-resolution data processing, can become resource-intensive [9], [10], [14]. For practical deployment, especially in large-scale urban systems, models need to strike a balance between accuracy and efficiency. Exploring lightweight architectures or edge-based processing could be one possible direction, though it comes with its own set of challenges [15].

In addition, the idea of incorporating user-centric factors into routing decisions feels somewhat underdeveloped. Most current systems focus on minimizing time, but future work could consider aspects like ride comfort, safety, or even vehicle type. For example, a route suitable for a heavy vehicle might differ from one preferred by a two-wheeler, especially when road conditions are taken into account [14], [16].

Finally, there is scope for improving evaluation methodologies. Many studies rely on limited or controlled datasets, which makes it difficult to assess how well the models would perform in real-world scenarios [11], [17]. Developing standardized benchmarks that include diverse environmental conditions could help in comparing approaches more fairly and pushing the field toward more practical solutions [18].

Overall, future research doesn't necessarily need to reinvent individual components, but rather find ways to connect them more effectively. The shift from isolated models to integrated, context-aware systems seems to be the direction where meaningful progress can happen [19], [20].

IV. CONCLUSION

Looking back at the studies discussed throughout this paper, it becomes fairly clear that the field has made meaningful progress, just not always in a connected way. Pothole detection techniques have improved steadily, especially with the adoption of deep learning models that are capable of identifying road surface irregularities with increasing accuracy [1]–[4], [10]. At the same time, routing and traffic prediction systems have also evolved, becoming more adaptive and responsive to real-time conditions through approaches like graph-based learning and reinforcement strategies [12]–[15].

Even so, these advancements seem to be moving along parallel paths rather than converging. Detection models focus on identifying and sometimes analyzing road conditions, while routing systems continue to prioritize travel time and congestion [15], [16]. The interaction between these two—where road condition insights could directly influence routing decisions—remains limited in the current body of work [5], [9], [18].

Another aspect that stands out is the difference between experimental performance and real-world applicability. Many models report strong results under controlled conditions, but fewer studies explore how these systems behave in dynamic and unpredictable environments [3], [11]. Issues such as scalability, computational overhead, and environmental variability still pose challenges, especially when considering real-time deployment [10], [13].

Taken together, the literature suggests that while individual components of intelligent transportation systems are becoming more capable, their integration is still incomplete. There is a growing need to move beyond isolated improvements and toward more unified frameworks that can combine traffic dynamics with road condition awareness [17], [20].

In that sense, this paper doesn't attempt to present a final solution, but rather to bring clarity to the current state of research and highlight where the gaps lie. The direction forward seems to involve not just improving accuracy or efficiency in isolation, but finding ways to make these systems work together more effectively—so that routing decisions are informed not only by how fast a route is, but also by how suitable it is for real-world travel conditions.

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