INTERNATIONAL JOURNAL OF NEXT-GENERATION
ENGINEERING AND TECHNOLOGY (IJNGET)

eISSN: 3087-4319
Volume. 03, Issue. 04, pp. 14-25, April 2026

Deep Learning and Intelligent Control in High-Stakes Systems: An Integrative Research Study on Lung Cancer CT Diagnosis and AI-Enabled Electric Vehicle Grid Management

Dr. Eleanor M. Whitford
School of Computational Engineering and Applied Intelligence, University of Bristol, United Kingdom

Article received: 21/02/2026, Article Accepted: 18/03/2026, Article Published: 17/04/2026

ABSTRACT

This article develops an original, publication-ready research study based strictly on the supplied references and examines two rapidly advancing but structurally comparable domains of intelligent decision-making: lung cancer detection from computed tomography imagery and electric vehicle integration into modern power systems. Although these domains differ in application, both represent high-stakes environments in which data-driven systems must operate under uncertainty, manage complex patterns, and support decisions with substantial human, societal, and infrastructural consequences. The medical studies in the provided corpus emphasize convolutional neural networks, transfer learning, hybrid deep learning methods, attention-based false-positive reduction, hyperparameter optimization, and validated predictive models for lung cancer screening, detection, segmentation, and risk prediction (Al-Huseiny & Sajit, 2021; Sun et al., 2021; Mikhael et al., 2023; Musthafa et al., 2024; Abe et al., 2025). The energy studies focus on reinforcement learning, deep reinforcement learning, vehicle-to-grid scheduling, voltage support, EV fleet services, charging coordination, renewable integration, and intelligent charging station design (Sortomme & El-Sharkawi, 2011; Richardson et al., 2012; Chen et al., 2022; Papadopoulos et al., 2023; Liu et al., 2023; Mohan et al., 2025).

Using a qualitative integrative methodology, this article synthesizes the conceptual, methodological, and operational patterns across these sources. The results reveal four dominant findings. First, both fields are moving from rule-based or isolated optimization toward adaptive, data-driven intelligence. Second, performance gains increasingly depend on architecture refinement, feature engineering, transfer learning, and optimization rather than on simple algorithm substitution alone. Third, deployment success in both domains depends not only on accuracy or efficiency, but also on reliability, interpretability, and management of false positives, uncertainty, and resource constraints. Fourth, the comparative reading of the literature suggests that health and energy systems are converging around a shared paradigm of intelligent socio-technical infrastructure in which machine learning functions as a coordinating rather than merely predictive tool. The discussion interprets these patterns, identifies limitations of current approaches, and proposes a future research agenda centered on trustworthy, interoperable, and domain-sensitive intelligence. The study concludes that the most meaningful future advances will come from frameworks that combine technical performance with system-level accountability in both medical imaging and EV-grid ecosystems.

Keywords: Lung cancer detection, computed tomography, deep learning, electric vehicle charging, reinforcement learning, vehicle-to-grid, intelligent systems.

INTRODUCTION

Artificial intelligence and machine learning are no longer confined to experimental or narrowly computational settings. They are increasingly embedded in domains where decisions carry direct implications for survival, infrastructure stability, public welfare, and long-term societal planning. The reference set supplied for this article brings together two such domains: medical image-based lung cancer detection and intelligent electric vehicle integration within modern power grids. At first glance, these may appear unrelated. One concerns disease diagnosis from computed tomography images, while the other concerns charging coordination, vehicle-to-grid interactions, grid services, and energy management. Yet a closer analysis reveals a meaningful commonality. In both cases, machine intelligence is being used to convert complex, high-dimensional, uncertain input into timely and consequential action. In both cases, the operational environment is dynamic rather than static. In both cases, the cost of error is high. Most importantly, in both cases, the literature reveals that the real problem is not merely whether AI can perform a task, but how it can be integrated responsibly into systems that must remain accurate, adaptive, and trustworthy under practical constraints.

The medical side of the literature focuses predominantly on lung cancer detection, recognition, diagnosis, nodule segmentation, false-positive reduction, and future risk prediction using deep learning and related approaches. Lung cancer remains one of the most serious clinical challenges in modern medicine because early-stage detection is often difficult, disease progression can be rapid, and diagnostic ambiguity may reduce the window for effective intervention. CT imaging has become a central modality in this context because it offers detailed visual information about pulmonary anatomy and suspected lesions. However, CT imaging also presents significant interpretive complexity. Nodules vary in size, location, morphology, contrast, and surrounding tissue context. Benign and malignant patterns may overlap visually. Imaging artifacts and class imbalance complicate model development and clinical interpretation. The supplied references collectively reflect this complexity through a range of approaches including convolutional neural networks, transfer learning, DenseNet-based architectures, hybrid deep learning, attention-embedded systems, preprocessing enhancement, feature selection, and risk prediction models (Al-Yasriy et al., 2020; Al-Huseiny & Sajit, 2021; Zhang et al., 2021; Sun et al., 2021; Javed et al., 2024; Zafar et al., 2024; Abe et al., 2025).

This literature also shows a developmental trajectory. Early and intermediate work often focused on the question of whether machine learning and deep learning could detect lung cancer or classify CT-based patterns with acceptable performance. More recent studies increasingly focus on how to refine these models to make them more robust, less error-prone, and more clinically meaningful. This is evident in the movement from generic CNN-based diagnosis toward transfer learning with GoogLeNet, attention-embedded complementary stream architectures for reducing false positives, optimized double-layered CNNs using advanced preprocessing and hyperparameter tuning, and validated risk-prediction systems such as Sybil that attempt not merely to classify an image but to anticipate future cancer risk from a single low-dose CT scan (Al-Huseiny & Sajit, 2021; Sun et al., 2021; Musthafa et al., 2024; Mikhael et al., 2023). Such developments indicate that the field is evolving from proof-of-concept AI toward clinically oriented intelligent support.

The healthcare references also contain a broader context beyond lung cancer alone. Studies on breast cancer prediction from multimodal datasets and on machine learning for enhancing cancer detection and prevention mechanisms show that lung cancer research belongs to a wider movement in medical intelligence, where diagnostic support increasingly draws upon complex data patterns across modalities and disease classes (Mishra et al., 2024; Sathya & Rohini, 2025). Although the present article remains centered on lung cancer because that is where the majority of the clinical references converge, these adjacent works help highlight a broader methodological reality: AI in healthcare is increasingly concerned with robust pattern discovery, multimodal inference, and domain-specific optimization rather than with a single universal algorithm.

The energy side of the provided literature focuses on another domain undergoing rapid transformation. Electric vehicles are no longer marginal elements within transportation and power planning. Their growing presence introduces new operational burdens and new opportunities for distribution networks, demand response programs, renewable integration, ancillary services, and localized voltage support. Traditional power systems were not designed around large mobile electrical loads capable of both consuming and, in some cases, returning energy to the grid. As EV penetration increases, the central engineering challenge becomes coordination. When should vehicles charge? How should fleets be scheduled? How can vehicle-to-grid interactions support grid reliability without undermining user requirements? How can charging be aligned with renewable generation and grid constraints? What role can reinforcement learning and data-driven control play in these environments? The supplied references address these questions through studies of optimal scheduling, localized reactive power control, smart charging reviews, reinforcement learning for renewable-integrated scheduling, deep reinforcement learning for demand response, and data-driven EV fleet control for grid services (Sortomme & El-Sharkawi, 2011; Richardson et al., 2012; Wen et al., 2022; Chen et al., 2022; Zhang et al., 2021; Papadopoulos et al., 2023; Liu et al., 2023).

This literature also suggests an evolution similar to what is seen in medical AI. Initial research concentrated on optimization of scheduling and power support under relatively structured conditions. Later studies increasingly turn toward reinforcement learning, deep reinforcement learning, hybrid energy management, open-access trading contexts, intelligent charging stations, and IoT-based battery control (Thenmozhi et al., 2022; Tirivikiraman et al., 2022; Ramesh et al., 2024; Mohan et al., 2025). This progression reflects a shift from deterministic control toward adaptive intelligence in environments characterized by uncertainty, distributed agents, variable renewable supply, and competing operational objectives. The inclusion of broader infrastructure sources, such as the E.DSO technical perspectives on EV integration with distribution grids, indicates that these developments are not merely academic but aligned with systemic transformation in energy networks (E.DSO, 2020).

The central claim of this article is that these two literatures, despite their domain differences, can be fruitfully understood through a shared conceptual lens. Both lung cancer diagnosis and EV-grid coordination are instances of high-stakes intelligent systems. In both fields, AI is asked to process large, complex, noisy, or uncertain inputs. In both, the goal is not just classification or prediction in an abstract sense, but timely support for real decisions under constraints. In healthcare, the system must distinguish suspicious from non-suspicious imaging features, reduce false positives, enable early diagnosis, and potentially stratify risk. In energy systems, the system must coordinate charging, respond to grid states, align with renewable variability, support voltage and ancillary services, and handle fleet-level uncertainty. In both cases, the central tension is between technical optimization and operational trustworthiness.

This shared lens is important because it helps move beyond superficial comparisons. The point is not to collapse healthcare and energy into the same problem. Their ethical, regulatory, temporal, and physical realities differ substantially. Rather, the point is that both fields illuminate what happens when machine learning matures from an analytical technique into infrastructure logic. Once AI becomes responsible for screening patients or coordinating fleets of distributed energy assets, questions of architecture, optimization, validation, robustness, interpretability, and domain adaptation become unavoidable. The provided references make clear that these questions already shape current research.

There is also a literature gap that justifies the present study. Reviews typically remain within disciplinary boundaries. Lung cancer imaging studies discuss transfer learning, segmentation, feature reduction, hybrid architectures, and validated risk models, but they do so within a medical AI frame (Javed et al., 2024; Sinjanka et al., 2024). EV charging studies discuss reinforcement learning, grid services, demand response, and V2G coordination within a smart-grid or power systems frame (Wen et al., 2022; Papadopoulos et al., 2023). What is largely missing is an integrative research perspective that compares these bodies of work as parallel examples of intelligent decision systems in high-stakes contexts. Such a comparison is useful because it reveals recurring design principles that transcend individual domains: reliance on data quality, architecture specialization, optimization under uncertainty, management of false positives or inefficient actions, and the growing need for reliable deployment rather than purely laboratory performance.

This article therefore pursues four objectives. First, it synthesizes the supplied literature on lung cancer detection and CT-based diagnosis through deep learning and machine learning methods. Second, it synthesizes the supplied literature on EV smart charging, grid integration, vehicle-to-grid services, and intelligent charging control. Third, it compares these domains at the level of system architecture, operational constraints, and intelligence design. Fourth, it develops a conceptual argument that future progress in both areas will depend not only on technical performance, but on trustworthy system integration.

The article is structured as a continuous academic document. The methodology explains the qualitative integrative approach used to derive findings strictly from the supplied sources. The results section presents descriptive patterns emerging from the two literatures and from their comparative interpretation. The discussion explores deeper implications, limitations, and future directions. The conclusion synthesizes the study’s central contributions and proposes a forward-looking research perspective. Through this structure, the article aims to contribute an original and publication-ready account of how AI is being shaped by, and in turn reshaping, two of the most consequential technical domains of the present era.

Methodology

This study adopts a qualitative integrative research design based strictly on the references provided in the prompt. The methodological approach is interpretive and synthetic rather than experimental, quantitative, or meta-analytic. This choice is necessary because the supplied literature includes heterogeneous source types, different domain aims, varied datasets, different evaluation conditions, and studies that are not directly comparable through a single statistical framework. Some papers address lung cancer detection and CT image analysis, others focus on broader cancer-related machine learning questions, and still others examine electric vehicle charging, grid services, reinforcement learning, or infrastructure-level integration. Accordingly, the task of the present article is not to produce pooled numerical estimates, but to organize and interpret the references into a coherent scholarly contribution.

The first methodological step involved corpus delimitation. The supplied references were examined to identify their principal domains, recurring themes, and cross-domain relevance. This examination showed that the literature falls into two primary clusters. The first cluster concerns lung cancer detection, classification, recognition, segmentation, and related medical imaging or cancer-oriented AI research. This includes dataset-oriented work, CNN-based classification, transfer learning, attention mechanisms, hybrid deep learning, hyperparameter optimization, validated risk models, and review-based analytical frameworks (Al-Yasriy & Al-Huseiny, 2021; Al-Huseiny & Sajit, 2021; Sun et al., 2021; Mikhael et al., 2023; Javed et al., 2024; Musthafa et al., 2024; Abe et al., 2025). The second cluster concerns electric vehicle integration with power systems, including smart charging, reinforcement learning, deep reinforcement learning, fleet control, demand response, localized voltage support, vehicle-to-grid services, charging station design, battery charge control, and hybrid energy management (Sortomme & El-Sharkawi, 2011; Richardson et al., 2012; Wen et al., 2022; Chen et al., 2022; Papadopoulos et al., 2023; Liu et al., 2023; Mohan et al., 2025).

The second methodological step involved thematic coding within and across these clusters. The coding process was inductive. Rather than imposing a single preexisting model, the study derived key analytical categories from the content and focus of the references themselves. For the medical AI cluster, the dominant themes were data foundations, CT image processing, nodule detection, cancer classification, transfer learning, false-positive reduction, hybrid deep learning, feature optimization, early diagnosis, and risk prediction. For the EV-grid cluster, the dominant themes were charging scheduling, vehicle-to-grid interaction, demand response, renewable integration, grid services, reactive power support, fleet coordination, data-driven control, hybrid energy management, and infrastructure design. Across both clusters, shared meta-themes emerged: adaptive intelligence, uncertainty management, optimization, architecture refinement, operational trust, and deployment-oriented performance.

The third methodological step was internal synthesis within each domain. In the medical AI cluster, the study examined how the literature evolves from foundational image-based classification efforts toward increasingly refined architectures. For example, early CNN-based diagnosis from CT scans established the feasibility of automated detection, while later work introduced transfer learning, DenseNet-based segmentation, complementary attention streams, hybrid deep learning, and optimization-heavy designs to improve robustness and reduce false positives (Al-Yasriy et al., 2020; Al-Huseiny & Sajit, 2021; Zhang et al., 2021; Sun et al., 2021; Wankhade & V. S., 2023; Musthafa et al., 2024). The review papers were used to contextualize these trends rather than substitute for them (Javed et al., 2024; Sinjanka et al., 2024). In the EV cluster, a similar synthesis traced the movement from foundational scheduling and voltage-support logic toward reinforcement learning, deep reinforcement learning, fleet-level control, renewable-aware charging, and hybrid intelligent charging station design (Sortomme & El-Sharkawi, 2011; Richardson et al., 2012; Chen et al., 2022; Zhang et al., 2021; Liu et al., 2023; Mohan et al., 2025).

The fourth methodological step was comparative synthesis across domains. This stage is central to the originality of the article. The study did not assume that lung cancer diagnosis and EV charging coordination are the same kind of problem. Instead, it asked whether the literature reveals common structural features in how machine intelligence is deployed under consequential conditions. The answer, derived from the references, is affirmative. In both domains, progress depends on domain-specific data quality, architecture adaptation, intelligent optimization, uncertainty handling, and reduction of costly errors. In medical imaging, false positives, missed detections, and poor generalization threaten clinical usefulness (Sun et al., 2021; Zafar et al., 2024; Abe et al., 2025). In EV-grid systems, poorly timed charging, inadequate demand response, and uncoordinated fleet behavior threaten grid stability and resource efficiency (Richardson et al., 2012; Papadopoulos et al., 2023; Liu et al., 2023). Comparative synthesis therefore focused on shared principles rather than identical application goals.

The fifth step involved contextual interpretation. Some references in the provided list are adjacent rather than central to the two major clusters. For instance, breast cancer prediction, heart disease risk prediction, and hybrid electric vehicle design are not primary sources for the main comparative axis, yet they are not irrelevant (Sathya & Rohini, 2025; Srija et al., 2025; Babu & Nenavath, 2025). These sources were interpreted contextually. The medical adjacent references support the broader claim that intelligent disease detection increasingly extends beyond a single disease class, suggesting wider movement toward multimodal and cross-disease machine learning in healthcare. The engineering adjacent references support the idea that EV intelligence is situated within a larger ecosystem of hybrid vehicle design, charging infrastructure, and energy coordination. This contextual reading remained conservative: no claim was made beyond what these sources reasonably support.

The sixth methodological step was conceptual framing. From the cumulative patterns in the references, the study developed a cross-domain conceptual frame: intelligent high-stakes systems. This concept refers to systems in which machine learning is used not merely for descriptive analytics, but for decision support or control in contexts where errors have substantial human or infrastructural consequences. The concept is useful because it captures what the two domains share without erasing their differences. In healthcare, the stakes concern delayed diagnosis, overtreatment, missed lesions, and patient risk. In power systems, the stakes concern grid congestion, voltage instability, poor renewable utilization, and inefficient coordination of large mobile loads. The frame allowed the article to treat both domains as examples of a broader transformation in engineering and applied intelligence.

To preserve evidentiary discipline, the study followed a strict source-bound rule: all substantive claims had to be grounded in one or more supplied references. No external literature, unsupported empirical values, or invented experiments were introduced. Where the article makes broader interpretive claims, those claims are explicitly based on patterns across the supplied corpus rather than on external authority. This matters because the prompt requires the article to be based strictly on the provided references.

The chosen methodology has several strengths. It enables integration of heterogeneous sources into a coherent academic narrative. It supports cross-domain comparison without pretending that the domains are empirically identical. It also allows theoretical insight to emerge from disciplinary juxtaposition. At the same time, it has limits. Because it is qualitative, it cannot produce pooled performance metrics or standardized rankings of models. Because the source list spans different fields, the comparative argument depends on structural interpretation rather than direct experimental comparison. These are real limitations, but they do not invalidate the method. Instead, they define its proper contribution: a rigorous, text-based synthesis that clarifies emerging patterns and proposes a conceptually useful framework for future research.

Through this methodology, the article identifies recurring patterns of architectural refinement, optimization, and intelligent coordination across medical imaging and EV-grid management. The results that follow are therefore not raw measurements but disciplined interpretive findings derived from the source literature.

Results

The integrative analysis of the supplied references yields a set of descriptive findings that are internally strong within each domain and analytically revealing across domains. The most prominent result is that both lung cancer detection research and EV-grid intelligence research are moving decisively away from static, rule-based, or narrowly optimized frameworks toward adaptive, data-driven, and context-sensitive systems. This shift is not uniform, but it is unmistakable across the source set.

Within the lung cancer literature, the first major result is the centrality of CT-based deep learning as the dominant technical paradigm for modern diagnostic support. Earlier and foundational work in the reference set demonstrates the feasibility of detecting or diagnosing lung cancer from CT scans using convolutional neural networks and related machine learning approaches (Al-Yasriy et al., 2020; B. S. et al., 2022). These studies establish that image-based computational methods can identify clinically relevant patterns in pulmonary scans that may otherwise demand substantial radiological attention and expertise. However, the later literature shows that feasibility alone is no longer the main concern. Instead, the field has shifted toward increasing robustness, improving detection across varying image conditions, and addressing common diagnostic pain points such as false positives, weak generalization, and difficult lesion localization.

This trend is visible in the move toward transfer learning, more specialized networks, and complementary architectural strategies. Al-Huseiny and Sajit (2021) demonstrate the relevance of transfer learning with GoogLeNet, suggesting that repurposing established image models for medical tasks can improve performance while reducing the need to train entirely new models from scratch. Zhang et al. (2021) extend the problem beyond simple classification by combining adaptive-hull methods with DenseNet-based convolutional architectures for automatic detection and segmentation of lung nodules in different anatomical locations. This is significant because the clinical challenge is not simply identifying whether a scan is abnormal, but locating relevant structures in diverse spatial contexts. Sun et al. (2021) take the further step of targeting false-positive reduction with an attention-embedded complementary-stream CNN, highlighting that clinical usability depends not only on sensitivity but also on limiting misleading alerts that burden clinicians and patients alike.

A second major result within the lung cancer literature is the increasing emphasis on optimization and hybridization. Musthafa et al. (2024) explicitly link classification efficiency to hyperparameter optimization and advanced image preprocessing, indicating that the architecture itself is only one part of performance. Wankhade and V. S. (2023) propose a novel hybrid deep learning method for early detection, while Zafar et al. (2024) emphasize enhanced detection and classification through an mRMR-based hybrid deep learning model. These studies collectively suggest that model performance in lung cancer diagnosis is no longer primarily improved by choosing a different single model family, but by carefully combining architectures, improving feature selection, and optimizing learning conditions. This is an important result because it shows that the field has entered a refinement phase, where gains are extracted from design detail rather than from general enthusiasm for deep learning.

A third major result is that the literature increasingly recognizes the importance of early detection and future-oriented prediction rather than solely retrospective classification. Mikhael et al. (2023) are especially notable in this regard because Sybil is described as a validated deep learning model capable of predicting future lung cancer risk from a single low-dose chest CT. This significantly expands the conceptual horizon of lung cancer AI. Instead of asking only whether an image already contains classifiable disease, the field is now exploring how current imaging patterns can be used to estimate future disease emergence. The theoretical implication is profound: AI is being positioned not just as a diagnostic assistant, but as a risk stratification tool that may reshape screening logic and early intervention strategies.

A fourth major result is that the literature remains highly dependent on data quality and dataset infrastructure. The IQ-OTHNCCD lung cancer dataset provided by Al-Yasriy and Al-Huseiny (2021) plays a foundational role in this respect. The existence of specialized, curated data resources is a precondition for training and validating machine learning systems in medical imaging. This result may seem obvious, but the reference set makes clear that the sophistication of models cannot be separated from the quality, representativeness, and accessibility of datasets. The CT-based lung cancer field is therefore as much a data engineering problem as it is a model design problem. Related work on SVM performance in marked CT datasets and review-based frameworks for early detection reinforces the importance of dataset properties and feature representation (Kareem et al., 2021; Sinjanka et al., 2024).

A fifth result is that lung cancer detection research increasingly sits within a broader medical AI movement toward disease intelligence rather than isolated lesion detection. Mishra et al. (2024) discuss advanced machine learning approaches for enhancing cancer detection and prevention mechanisms more generally, while Sathya and Rohini (2025) address breast cancer prediction from multimodal datasets. Although these are not lung-specific, they support the interpretation that medical AI is becoming more integrative, more data-diverse, and more prevention-oriented. Lung cancer work in the supplied references therefore appears as part of a wider transformation in computational medicine.

Within the EV and power systems literature, the first major result is the growing centrality of intelligent scheduling and adaptive charging management. Sortomme and El-Sharkawi (2011) provide foundational work on the optimal scheduling of vehicle-to-grid energy and ancillary services. Richardson et al. (2012) extend this logic into localized reactive power control for voltage support with electric vehicles. These studies indicate that the EV is not merely a transportation device from the grid's perspective, but an active participant in energy coordination. The result here is foundational: the problem of EV integration is not simply one of load accommodation, but one of dynamic participation in grid services.

A second major result in the EV literature is the strong movement toward reinforcement learning and deep reinforcement learning as coordination paradigms. Chen et al. (2022) examine reinforcement learning for charging scheduling with renewable integration, while Zhang et al. (2021) explore deep reinforcement learning for EV fleet demand response under uncertainty. Papadopoulos et al. (2023) further develop this line through deep reinforcement learning for V2G-enabled demand response. Together, these studies show that the complexity of EV-grid systems increasingly exceeds what static optimization alone can elegantly manage. Renewable variability, uncertain vehicle availability, time-varying demand, user expectations, and multi-agent coordination create a decision environment well suited to learning-based control. This is one of the clearest parallels with the lung cancer literature: in both fields, intelligent systems are advancing not because static methods are useless, but because the real-world environment is too dynamic for rigid strategies to remain sufficient.

A third result is the increasing importance of fleet-level and system-level control. Liu et al. (2023) address data-driven control of EV fleets for grid services, and Ramesh et al. (2024) incorporate EV fleets into optimal power flow with open-access trading of wind farms. These sources indicate that the field has moved beyond individual charging logic toward coordinated fleet orchestration within broader electricity markets and system operations. This is a major conceptual development. It implies that the relevant unit of intelligence is no longer just the vehicle, but the distributed fleet embedded in a multi-resource energy ecosystem.

A fourth major result concerns integration with renewable energy and broader energy management. Chen et al. (2022) explicitly connect charging scheduling with renewable integration. Thenmozhi et al. (2022) discuss hybrid energy management on electric vehicles for power grids with renewable systems. Wen et al. (2022), in reviewing AI applications in smart charging, reinforce the relevance of intelligent methods in managing these complexities. This result is particularly important because it demonstrates that EV intelligence is not merely about efficiency or convenience. It is increasingly about aligning transportation electrification with energy transition goals. The smarter the charging strategy, the more feasible it becomes to integrate variable renewable resources without destabilizing the grid or wasting available clean energy.

A fifth result in the EV domain is that infrastructure intelligence extends beyond abstract control algorithms into practical platform design. Tirivikiraman et al. (2022) focus on smart battery charge control using LabVIEW with an IoT platform. Mohan et al. (2025) examine the design and implementation of an EV charging station integrated with different energy sources using an ANFIS controller. Babu and Nenavath (2025), though oriented toward hybrid electric vehicle design rather than charging control specifically, support the wider view that EV intelligence exists in an ecosystem of vehicle architecture, interface systems, and power management. The result here is that algorithmic intelligence must eventually be realized through hardware, platforms, interfaces, and coordinated infrastructure design.

When the two domains are examined together, a series of cross-domain results emerges. The first cross-domain result is that both fields rely on domain-specific data pipelines rather than generic learning alone. In medical imaging, CT datasets and lesion annotation structures are indispensable (Al-Yasriy & Al-Huseiny, 2021). In EV-grid systems, time-series data on fleet behavior, demand conditions, renewable generation, and network constraints are equally central (Liu et al., 2023; Wen et al., 2022). In both fields, the quality and organization of data shape the ceiling of model performance.

The second cross-domain result is that architecture specialization matters more than generic algorithm identity. A CNN is not sufficient in itself; the literature favors transfer learning, attention embedding, DenseNet coupling, hybridization, preprocessing enhancement, and hyperparameter tuning for clinical relevance (Sun et al., 2021; Musthafa et al., 2024; Zafar et al., 2024). Likewise, reinforcement learning is not sufficient in itself; the literature increasingly emphasizes deep reinforcement learning, renewable-aware scheduling, V2G-enabled demand response, and fleet-specific control (Chen et al., 2022; Zhang et al., 2021; Papadopoulos et al., 2023). This result suggests that AI maturity in both domains is expressed through contextual tailoring.

The third cross-domain result is that uncertainty management is central. In lung cancer detection, uncertainty appears in ambiguous nodules, noisy imaging, class imbalance, future risk prediction, and false positives. In EV-grid coordination, uncertainty appears in vehicle arrival and departure patterns, user charging behavior, renewable generation volatility, demand fluctuations, and open market conditions. The literature from both domains therefore converges on the need for models that remain effective when input patterns are incomplete, shifting, or difficult to interpret.

The fourth cross-domain result is that operational usefulness depends on minimizing costly mistakes, not merely maximizing abstract performance. In medicine, a false positive can lead to unnecessary follow-up, anxiety, and clinical burden, while a false negative may delay treatment. This concern is directly reflected in work focused on false-positive reduction and enhanced classification robustness (Sun et al., 2021; Abe et al., 2025). In EV systems, poor control decisions can produce peak congestion, underused renewable supply, voltage issues, or inefficient grid services (Richardson et al., 2012; Papadopoulos et al., 2023; Liu et al., 2023). In both domains, the literature reflects a transition from model-centric evaluation to consequence-aware evaluation.

The fifth cross-domain result is that both literatures point toward intelligent infrastructure rather than isolated intelligent models. Lung cancer AI increasingly appears as part of a screening and risk-stratification ecosystem. EV intelligence increasingly appears as part of a distributed, renewable-connected, service-oriented grid ecosystem. This finding is perhaps the most important of the entire study because it suggests that the future of AI in high-stakes domains lies not in stand-alone accuracy, but in system integration.

Discussion

The results of this study reveal a deeper transformation occurring across advanced applied intelligence. Both lung cancer CT diagnosis and EV-grid management demonstrate that AI is moving beyond narrow prediction tasks and becoming embedded within decision infrastructures. This shift has major theoretical implications. It means that model performance, while still essential, can no longer be treated as the sole measure of progress. Instead, progress increasingly depends on how models are integrated into workflows, how they respond to uncertainty, how they handle costly error, and how well they align with domain-specific realities.

In lung cancer diagnosis, one of the clearest lessons of the literature is that detection accuracy is only one dimension of usefulness. Early work proved that CNN-based systems could identify suspicious patterns in CT images, but later research increasingly targeted the practical limitations that block clinical adoption. False positives are one such limitation. Sun et al. (2021) focus specifically on reducing false positives in pulmonary nodule detection, which is a highly consequential concern. A diagnostic system that flags too many benign findings may appear sensitive on paper, but it risks creating downstream inefficiency, patient anxiety, diagnostic overload, and lower clinician trust. This is why the trend toward attention mechanisms, complementary streams, hybrid models, and optimization is so important. These techniques signal a field grappling with the operational meaning of diagnostic intelligence rather than celebrating performance metrics in abstraction.

The move toward validated risk prediction, as seen in Mikhael et al. (2023), also indicates a broadening of what diagnostic AI is expected to do. Traditional image classification asks whether a lesion is present or whether a scan should be placed in one category or another. Risk prediction asks a more temporally ambitious question: what can current imaging reveal about future disease likelihood? This shift reflects a growing ambition in medical AI to become preventive and anticipatory. However, this shift also raises major questions. Risk prediction models may offer earlier warning and better screening prioritization, but they also introduce interpretive challenges. How should risk signals be communicated? What thresholds justify intervention? How robust are predictions across populations, imaging devices, and screening contexts? The literature provided does not resolve these questions fully, but it clearly shows that the field is moving toward them.

Another important implication from the medical literature is that no single architecture appears sufficient across all diagnostic tasks. Transfer learning helps when training data are limited or when pretrained vision systems can provide valuable feature extraction (Al-Huseiny & Sajit, 2021). DenseNet-based approaches help where segmentation and spatial representation are important (Zhang et al., 2021). Attention-based systems help where false-positive reduction demands selective emphasis (Sun et al., 2021). Hyperparameter optimization and preprocessing improve classification efficiency and robustness (Musthafa et al., 2024). Hybrid methods support better combination of representational strengths (Wankhade & V. S., 2023; Zafar et al., 2024). This plurality suggests that the future of lung cancer AI is not about discovering one universally superior model. It is about matching architectural logic to clinical need and imaging difficulty.

This conclusion has a parallel in the EV-grid literature. Here too, no single control method appears adequate for all situations. Foundational scheduling approaches and reactive power strategies remain important because they establish the physical and operational logic of EV participation in the grid (Sortomme & El-Sharkawi, 2011; Richardson et al., 2012). Yet as the environment becomes more dynamic, learning-based coordination gains importance. Reinforcement learning becomes attractive where the system must learn from interaction, adapt to variable conditions, and manage competing objectives over time (Chen et al., 2022). Deep reinforcement learning becomes especially relevant at the fleet level or under uncertainty, where state spaces become richer and control policies require more expressive capacity (Zhang et al., 2021; Papadopoulos et al., 2023). Data-driven fleet control and renewable-aware management represent further steps toward embedded operational intelligence (Liu et al., 2023; Thenmozhi et al., 2022).

The EV literature also demonstrates that intelligent control is inseparable from infrastructural context. In abstract optimization studies, a charging policy may appear elegant. In real grids, however, charging is constrained by network conditions, user habits, renewable availability, market structures, voltage considerations, and hardware capabilities. The inclusion of technical perspective documents and practical charging station design studies reinforces this point (E.DSO, 2020; Mohan et al., 2025). AI in this domain is therefore not merely a software solution. It is an infrastructural coordination mechanism. The same is increasingly true in medical imaging. A lung cancer model is not just an image classifier. It becomes part of a screening pathway, a clinician workflow, a patient management system, and potentially a risk stratification regime. This parallel is central to the article’s broader argument.

A particularly important theoretical contribution of the present study is the idea that both literatures reflect the rise of intelligent high-stakes systems. This concept matters because it helps explain why certain research features recur across both domains. One recurring feature is the premium placed on reducing harmful errors. In medicine, harmful errors include missed cancers and false alarms. In EV systems, they include instability, inefficient charging, poorly timed grid interaction, and underused renewable potential. Another recurring feature is the importance of domain-specific optimization. General-purpose machine learning is rarely enough. The best-performing systems in the supplied literature are those that adapt to the domain’s representational and operational structure. A third recurring feature is that system performance depends on both the intelligence core and the surrounding data or infrastructure environment.

This perspective also helps clarify why adjacent references in the corpus are meaningful rather than accidental. Breast cancer prediction, heart disease risk prediction, and general cancer detection research suggest that medical AI is increasingly moving toward disease ecosystems rather than isolated classification challenges (Mishra et al., 2024; Sathya & Rohini, 2025; Srija et al., 2025). Similarly, hybrid EV design, charging station architectures, and battery control studies suggest that smart charging intelligence sits within a larger ecosystem of vehicle, grid, and platform design (Babu & Nenavath, 2025; Tirivikiraman et al., 2022; Mohan et al., 2025). The implication is that intelligence migrates outward. It begins with a model but eventually reshapes system architecture.

There are, however, important cautionary points. One risk in both domains is technological overconfidence. In the medical field, high reported performance in controlled studies can obscure challenges of generalization, population diversity, imaging protocol variation, and real-world clinical workflow adoption. Review and framework studies imply that early detection is not just a technical classification task but an integrated analytical challenge involving data, interpretability, and screening strategy (Javed et al., 2024; Sinjanka et al., 2024). Similarly, in EV-grid systems, a reinforcement learning controller that performs well in simulation may face difficulties when confronted with real driver behavior, communication delays, hardware limitations, regulatory constraints, and conflicting incentives. The literature supplied suggests steady progress, but it does not justify assuming that optimization in research settings translates automatically into robust deployment.

A second caution concerns interpretability and trust. While the supplied references do not focus explicitly on explainable AI, the need for trust is implicit throughout both domains. Clinicians will not fully rely on models that generate unstable or opaque conclusions, especially when those conclusions affect cancer suspicion and follow-up decisions. Grid operators and infrastructure planners will likewise hesitate to rely on adaptive charging logic that produces efficient outcomes without transparent operational rationale. This does not mean that every deep model must become fully transparent in a simplistic sense. Rather, it means that trustworthiness must become part of performance thinking. A model that is accurate but operationally inscrutable may have limited adoption in high-stakes contexts.

A third caution concerns data dependency. The presence of specialized datasets in the medical literature and data-driven control in the EV literature underscores that intelligent systems are deeply dependent on the environments from which their data are drawn. If the data are biased, incomplete, unrepresentative, or poorly aligned with real deployment conditions, then model performance may be fragile. This issue is particularly serious in lung cancer detection, where CT datasets may differ by scanner settings, patient populations, annotation quality, and disease prevalence. It is also serious in EV coordination, where fleet behavior, charging habits, and renewable patterns vary across cities, regions, and grid infrastructures. The future of both fields therefore depends not only on algorithmic sophistication, but on sustained investment in representative, well-structured, and operationally relevant data ecosystems.

The discussion also suggests that convergence across domains may inspire useful methodological transfer, even if direct technical transfer is limited. For example, the strong concern with false-positive reduction in lung cancer detection could inspire analogous thinking in EV systems about the reduction of false control activations or poorly timed interventions. Conversely, the emphasis on adaptive sequential decision-making in reinforcement learning for EV charging may encourage more temporally aware strategies in medical screening and risk prediction, where repeated scans or longitudinal patient trajectories matter. The domains are not interchangeable, but comparative study may still illuminate underexplored design logic.

Another important implication concerns evaluation itself. The literature suggests that evaluation criteria in high-stakes AI should evolve from narrow technical metrics toward domain consequences. In lung cancer detection, it is not enough to ask whether a classifier identifies lesions. One must ask whether it reduces harmful misses, avoids burdensome false positives, supports earlier treatment, and functions across heterogeneous imaging conditions. In EV systems, it is not enough to ask whether a policy reduces charging cost or improves scheduling efficiency. One must ask whether it supports grid stability, aligns with renewable objectives, respects user needs, and remains robust under uncertainty. This domain-consequence orientation may be one of the most important methodological lessons emerging from the present synthesis.

The study has limitations that should be openly acknowledged. First, it is based strictly on the provided references and does not incorporate external literature, clinical validation studies beyond those listed, or broader power systems policy work. Second, the source list combines two different fields, which means the article’s originality lies in synthesis and comparison rather than in unified empirical testing. Third, because the evidence base is heterogeneous, no quantitative meta-analysis or common metric-based ranking is possible. Fourth, some references contain abbreviated author information or limited bibliographic detail, which constrains precise reconstruction of every underlying study design. These limits do not negate the study’s value, but they define its contribution correctly: this is an integrative conceptual research article, not a pooled trial analysis or engineering benchmark study.

These limitations also point to future research directions. In the medical domain, future work should focus on cross-dataset generalization, clinically meaningful false-positive reduction, multimodal fusion, longitudinal risk prediction, and workflow-integrated decision support. Studies like Mikhael et al. (2023), Musthafa et al. (2024), and Abe et al. (2025) suggest that the field is ready for more deployment-oriented research rather than merely architecture competition. In the EV domain, future work should emphasize real-world fleet coordination, renewable-aware adaptive scheduling, interoperable infrastructure control, user-centered V2G strategies, and integration between algorithmic intelligence and practical charging station architectures. Works such as Chen et al. (2022), Liu et al. (2023), Papadopoulos et al. (2023), and Mohan et al. (2025) imply that the field is moving from optimization experiments toward infrastructure intelligence.

At a broader level, future research across both domains should address trust, governance, and reliability as first-class concerns. The most significant advances may not come from marginal gains in benchmark performance alone. They may come from systems that remain robust under real conditions, are understandable to domain experts, and integrate cleanly into operational environments. In both medicine and energy, the future of AI will be shaped less by novelty in isolation and more by responsible performance in context.

The comparative perspective of this article therefore supports a wider conclusion. High-stakes AI is not defined by the presence of a powerful model. It is defined by the successful alignment of data, architecture, uncertainty management, domain logic, and operational trust. The literature on lung cancer CT diagnosis and EV-grid intelligence, when read together, demonstrates this with remarkable clarity.

Conclusion

This article has presented an original integrative research study based strictly on the supplied references and has shown that lung cancer CT diagnosis and intelligent EV-grid management, despite belonging to different domains, share a deep structural resemblance as high-stakes intelligent systems. The literature on lung cancer detection reveals a field moving from initial feasibility toward refined, clinically oriented architectures emphasizing transfer learning, segmentation, hybrid deep learning, false-positive reduction, hyperparameter optimization, and risk prediction (Al-Huseiny & Sajit, 2021; Sun et al., 2021; Musthafa et al., 2024; Mikhael et al., 2023; Abe et al., 2025). The literature on electric vehicle integration reveals a field moving from foundational scheduling and grid support logic toward reinforcement learning, deep reinforcement learning, renewable-aware charging, fleet-level coordination, and intelligent charging infrastructure (Sortomme & El-Sharkawi, 2011; Richardson et al., 2012; Chen et al., 2022; Papadopoulos et al., 2023; Liu et al., 2023; Mohan et al., 2025).

The core conclusion is that progress in both fields increasingly depends on more than algorithmic power alone. It depends on data quality, domain-specific architecture design, uncertainty handling, and reduction of costly operational errors. In medicine, the challenge is not simply recognizing suspicious CT patterns, but doing so in a way that supports early diagnosis, reduces false positives, and enables meaningful risk assessment. In energy systems, the challenge is not simply scheduling charging events, but doing so in a way that supports grid stability, renewable integration, fleet coordination, and practical infrastructure deployment. These are not identical problems, but they are governed by a common logic of intelligent system design.

A second conclusion is that both domains are moving toward system integration rather than stand-alone model development. Lung cancer AI increasingly functions within broader screening, diagnosis, and prevention workflows. EV intelligence increasingly functions within broader smart-grid, charging infrastructure, and energy management ecosystems. This shift means that future research should place greater emphasis on trustworthiness, interoperability, and real-world deployment.

A third conclusion is that comparative research across high-stakes AI domains is valuable. It helps reveal shared design pressures that might remain less visible within a single discipline. The present study shows that healthcare and power systems both demand intelligent solutions that are adaptive, reliable, context-aware, and consequence-sensitive. That insight may support a more mature understanding of AI as infrastructure rather than as isolated computation.

Future research should therefore prioritize clinically grounded diagnostic intelligence in medical imaging, infrastructure-grounded adaptive control in EV systems, and broader frameworks for trustworthy machine learning in consequential settings. The references provided for this article strongly support the view that the future of intelligent systems will be determined not only by what models can compute, but by how responsibly and effectively they can act within the systems that depend on them.

References

1. Abe, A. A., Nyathi, M., Okunade, A. A., Pilloy, W., Kgole, B., & Nyakale, N. (2025). A robust deep learning algorithm for lung cancer detection from computed tomography images. Intelligence-Based Medicine, 11, 100203.

2. Al-Huseiny, M. S., & Sajit, A. S. (2021). Transfer learning with GoogLeNet for detection of lung cancer. Indonesian Journal of Electrical Engineering and Computer Science, 22(2), 1078–1086.

3. Al-Yasriy, H., & Al-Huseiny, M. (2021). The IQ-OTHNCCD lung cancer dataset (Version 2). Mendeley Data. https://doi.org/10.17632/bhmdr45bh2.2

4. Al-Yasriy, H. F., et al. (2020). Diagnosis of lung cancer based on CT scans using CNN. IOP Conference Series: Materials Science and Engineering, 928(2).

5. Babu, T. S., & Nenavath, P. (2025). Design and

development of hybrid electric vehicle. Journal of Next Generation Technology, 5(5), 63–74. https://www.jnxtgentech.com/volume-5-issues-5.php

6. B. S., P. R., & A. B. (2022). Lung cancer detection using machine learning. In 2022 Salem, India (pp. 539–543). https://doi.org/10.1109/ICAAIC53929.2022.9793061

7. Chen, Y., Li, X., & Wang, J. (2022). Reinforcement learning for electric vehicle charging scheduling with renewable integration. IEEE Transactions on Smart Grid, 13(2), 1025–1036.

8. E.DSO. (2020). Electric vehicle integration with distribution grids: Technical perspectives. European Distribution System Operators.

9. Javed, R., Abbas, T., Khan, A. H., et al. (2024). Deep learning for lungs cancer detection: A review. Artificial Intelligence Review, 57, 197.

10. Kareem, H. F., et al. (2021). Evaluation of SVM performance in the detection of lung cancer in marked CT scan dataset. Indonesian Journal of Electrical Engineering and Computer Science, 21(3), 1731.

11. Liu, H., Zhang, Q., & Xu, Y. (2023). Data-driven control of EV fleets for grid services. Applied Energy, 341, 121054.

12. Mikhael, P. G., et al. (2023). Sybil: A validated deep learning model to predict future lung cancer risk from a single low-dose chest computed tomography. Journal of Clinical Oncology, 41(12), 2191–2200.

13. Mishra, K. N., Mishra, A., Ray, S., Kumari, A., & Waris, S. M. (2024). Enhancing cancer detection and prevention mechanisms using advanced machine learning approaches. Informatics in Medicine Unlocked, 50, 101579.

14. Mohan, B., Ramesh, M. V., Moturu, P., et al. (2025). Design and implementation of electric vehicle charging station integrated with different energy sources using ANFIS controller. Journal of Theoretical and Applied Information Technology, 103(4).

15. Musthafa, M. M., Manimozhi, I., Mahesh, T. R., & Guluwadi, S. (2024). Optimizing double-layered convolutional neural networks for efficient lung cancer classification through hyperparameter optimization and advanced image pre-processing techniques. BMC Medical Informatics and Decision Making, 24(1), 142.

16. Papadopoulos, A., Kamboj, S., & Mathur, S. (2023). Deep reinforcement learning for V2G-enabled demand response. Electric Power Systems Research, 218, 109267.

17. Ramesh, M. V., et al. (2024). Improved skill optimization algorithm based optimal power flow considering open-access trading of wind farms and electric vehicle fleets. International Journal of Intelligent Engineering and Systems, 17(2), 370–382. https://doi.org/10.22266/ijies2024.0430.33

18. Richardson, D., Flynn, D., & Keane, A. (2012). Localized reactive power control for voltage support with electric vehicles. IEEE Transactions on Power Systems, 27(2), 1013–1021.

19. Sathya, R., & Rohini, P. (2025). Breast cancer prediction from multimodal datasets using deep learning techniques. Journal of Next Generation Technology, 5(2), 113–121.

20. Shatnawi, M. Q., Abuein, Q., & Al-Quraan, R. (2025). Deep learning-based approach to diagnose lung cancer using CT-scan images. Intelligence-Based Medicine, 11, 100188.

21. Sinjanka, Y., Kaur, V., Musa, U. I., et al. (2024). ML-based early detection of lung cancer: An integrated and in-depth analytical framework. Discover Artificial Intelligence, 4, 92.

22. Sortomme, E., & El-Sharkawi, M. (2011). Optimal scheduling of vehicle-to-grid energy and ancillary services. IEEE Transactions on Smart Grid, 3(1), 351–359.

23. Srija, G., Bhargavi, E., Sai Teja, G., Kotesh, B., Anusha, P., & Santhosh Kumar, B. (2025). Synthetic data generation and machine learning for enhanced heart disease risk prediction. Journal of Next Generation Technology, 5(5), 22–30.

24. Sun, L., et al. (2021). Attention-embedded complementary-stream CNN for false positive reduction in pulmonary nodule detection. Computers in Biology and Medicine, 133, 104357.

25. Thenmozhi, T., Suganyadevi, M. V., et al. (2022). Hybrid energy management on electric vehicles for power grids with renewables system. Environmental Challenges, 9, 100647. https://doi.org/10.1016/j.envc.2022.100647

26. Tirivikiraman, B., Sivaramakrishnan, S., Srikarthick, N., & Jegadeesan, M. (2022). Smart charge control of batteries in electric vehicle using LabVIEW with IoT platform. Journal of Next

Generation Technology, 2(1), 30–39.

27. Vemula, S. T., Sreevani, M., Rajarajeswari, P., Bhargavi, K., Tavares, J. M. R. S., & Alankritha, S. (2024). Deep learning techniques for lung cancer recognition. Engineering, Technology & Applied Science Research, 14(4), 14916–14922.

28. Wankhade, S., & V. S. (2023). A novel hybrid deep learning method for early detection of lung cancer using neural networks. Healthcare Analytics, 3, 100195.

29. Wen, Y., Yang, H., & Tang, Y. (2022). Review of AI applications in electric vehicle smart charging. Renewable and Sustainable Energy Reviews, 159, 112176.

30. Zafar, S., Ahmad, J., Mubeen, Z., & Mumtaz, G. (2024). Enhanced lung cancer detection and classification with mRMR-based hybrid deep learning model. Journal of Computing & Biomedical Informatics, 7(2).

31. Zhang, T., Wang, Y., & Zhou, X. (2021). Deep reinforcement learning for EV fleet demand response under uncertainty. Energy, 236, 121395.

32. Zhang, X., Li, S., Zhang, B., Dong, J., Zhao, S., & Liu, X. (2021). Automatic detection and segmentation of lung nodules in different locations from CT images based on adaptive-hull algorithm and DenseNet convolutional network. International Journal of Imaging Systems and Technology, 31(4), 1882–1893.