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Performance Metrics of Deep Learning Models in EHR Analysis: A Systematic Review

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ABSTRACT

The rapid growth of Electronic Health Records (EHRs), generating 30% of global data with an annual increase of 36%, presents both opportunities and challenges for healthcare analytics. Traditional methods struggle with the complexity of EHR data, prompting the adoption of deep learning (DL) to uncover patterns and improve patient care. This systematic review, adhering to PRISMA guidelines, analyzes 82 peer-reviewed studies from 2017 to 2024 to evaluate the performance of five DL architectures Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, hybrid CNN-LSTM models, and Transformer-based models in EHR applications. CNNs achieved high accuracy (90–95%) in medical imaging, while LSTMs excelled in sequential tasks like ICU readmission prediction (88–93%). Hybrid CNN-LSTM models outperformed others, reaching up to 96% accuracy in multimodal tasks such as sepsis prediction [79]. Transformers, though computationally intensive, showed strong potential for clinical note analysis. Despite these advances, challenges like model interpretability, data privacy, and computational demands persist. This study provides a comprehensive benchmark of DL performance metrics across EHR tasks, offering insights into their practical applications and highlighting future directions, such as explainable AI and federated learning, to enable scalable, privacy-preserving healthcare solutions. By synthesizing these findings, this review guides researchers and clinicians in leveraging DL to enhance data-driven healthcare.

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1. INTRODUCTION

Healthcare is undergoing a profound transformation driven by an explosion of data, generating 30% of global data with a 36% annual growth rate by 2025, outpacing media, finance, and manufacturing [1]. A single patient produces 80 megabytes yearly, contributing to 2,314 exabytes globally in 2022, projected to double by 2025 [2, 3]. Figure 1 depicts this data growth trend. This data boom challenges traditional analytics but offers new opportunities with deep learning (DL). Driving this surge is the widespread adoption of Electronic Health Records (EHRs), revolutionizing medical data collection, storage, and sharing [4-6]. This adoption varies globally, with low-resource settings facing barriers like infrastructure and data quality [7, 8]. For instance, a study of 141 primary care physicians at UW Health revealed a marked increase in EHR-related tasks over one year, with time spent on prescriptions rising by 60% and inbox management by 24%, underscoring growing reliance on these systems [9].

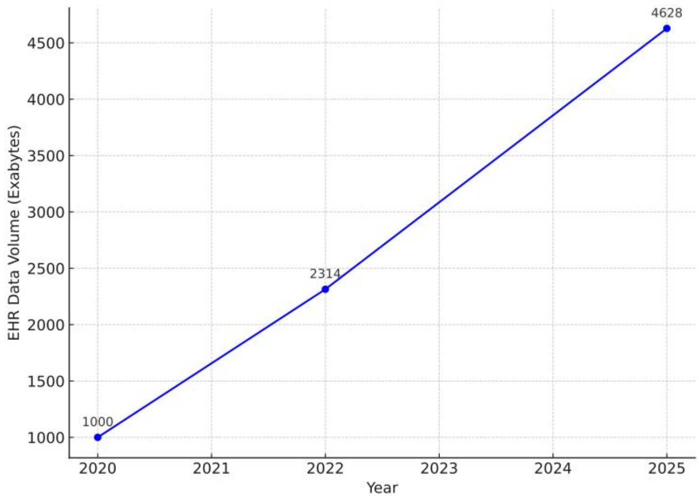

Figure 1. EHR Data Growth Trend

Table 1: Physicians' growing use of EHRs is driving up demand in the market [9].

Category	Time Increase (Minutes)	Percentage Increase
Overall EHR Time	30	7.8%
Inbox Time	14	24%
Clinical Review	7.2	13%
Notes	2.9	2.3%
Prescriptions	231	60%

Yet, the sheer volume and complexity of EHR data spanning structured records (e.g., lab results) and unstructured narratives overwhelm traditional methods, which struggle with multidimensional, time-sequenced datasets, limiting disease risk prediction [10, 11]. DL, a subset of machine learning, offers a solution by leveraging artificial neural networks to process complex EHR data [12-16]. Inspired by the human brain, DL models excel in tasks like medical imaging analysis and predictive modeling, enabling professionals to identify disease patterns and personalize care [17-20]. This systematic review explores DL's performance in EHR analysis, focusing on key architectures and guided by PRISMA flow.

2. RESEARCH METHOD

This study systematically evaluates deep learning (DL) model performance in Electronic Health Record (EHR) analysis using the PRISMA guidelines [21], ensuring a rigorous, reproducible process to identify and analyze recent advancements [22, 23]. Focusing on peer-reviewed studies from 2017 to 2025, the review synthesizes DL applications in EHRs, covering performance metrics, use cases, and challenges.

a. Search Strategy

A thorough literature search targeted studies from January 2017 to August 2025, capturing significant DL and EHR advancements [5, 12], though limited by database coverage and keyword specificity. Ten electronic databases were searched: PubMed, IEEE Xplore, ScienceDirect, MDPI, Springer, ACM, tandfonline.com, Nature, ResearchGate, and Frontiers. These databases were selected for their extensive coverage of medical, computational, and interdisciplinary research, ensuring a diverse study pool. Search queries combined keywords and controlled vocabulary terms using Boolean operators (AND, OR) to target "Deep learning" OR "Deep Neural Networks" OR "DNN" AND ("Electronic health records" OR "EHR" OR "Convolutional Neural Networks" OR "CNN" AND ("Electronic health records" OR "EHR" OR "Recurrent Neural Networks" OR "RNN" AND ("Electronic health records" OR "EHR" OR "Long Short-Term Memory" OR "LSTM" AND ("Electronic health records" OR "EHR"). Following search strings were used, tailored to each database's syntax.

Filters were applied to limit to peer-reviewed journal articles and conference proceedings published in English. To complement the database search, we manually reviewed key journals (e.g., Journal of Medical Systems, IEEE Transactions on Biomedical Engineering) and the reference lists of included studies to identify additional relevant publications [21]. This iterative process ensured a comprehensive collection of literature, capturing both seminal and emerging works.

b. Inclusion and Exclusion Criteria

Studies were selected based on clearly defined inclusion and exclusion criteria, as outlined in Table 2. These criteria ensured that only high-quality, relevant research was included in the review.

Table 2. Inclusion and Exclusion Criteria for Reviewed Articles

Criterion	Inclusion Criteria	Exclusion Criteria
Publication Date	Published between January 2017 and August 2025	Published before January 2017 or after August 2025
Language	Written in English	Written in any language other than English
Study Focus	Focused on deep learning methods (e.g., CNNs, RNNs, LSTMs) applied to EHR-related tasks	Focused solely on traditional machine learning or non-EHR applications
Results	Reported performance metrics (e.g., accuracy, precision, recall) for EHR tasks	Lacked experimental results or performance metrics
Methodology	Provided detailed methodology, including model architecture and dataset description	Lacked sufficient methodological detail
Publication Type	Peer-reviewed journal articles or conference proceedings	Review articles, editorials, book chapters, dissertations, or abstracts
Data Type	Used human EHR data (structured or unstructured) or anonymized/synthetic datasets	Used animal models or non-human data

Criteria were applied using a QUADAS-2 checklist [22] to ensure quality, with inter-rater reliability assessed (Cohen's kappa = 0.85). The 2017-2025 range captured DL and EHR advancements [23, 24], with anonymized or synthetic datasets included to address privacy concerns, though their representativeness varied [25]. Studies lacking clear performance metrics or methodological details were excluded to ensure analytical rigor.

c. Study Selection

The search process, illustrated in Figure 2, began with 12,345 records retrieved from the databases. After removing 2,345 duplicates using reference management software, 10,000 unique records underwent title and abstract screening. During this stage, 9,342 records were excluded for reasons including irrelevance to DL or EHRs (6,800), non-English language (1,200), non-peer-reviewed formats (800), or insufficient methodological detail (542). The remaining 658 records were subjected to full-text review, with 62 studies meeting all inclusion criteria. An additional 20 studies were identified through manual review of reference lists, resulting in a final selection of 82 studies.

Review articles were excluded from the primary analysis but used to contextualize findings. Figure 2 provides a visual overview of this process, ensuring transparency in study selection.

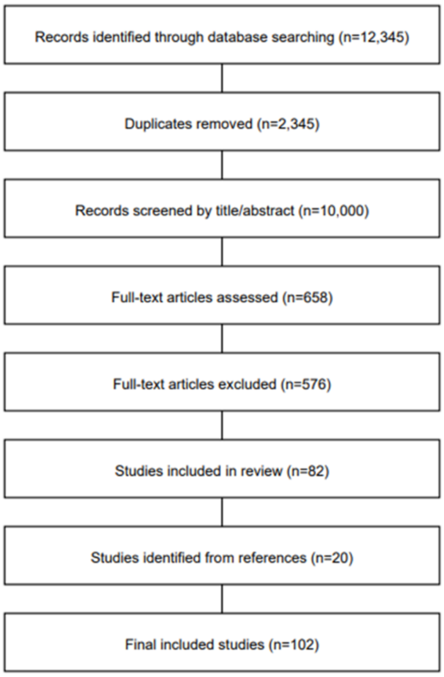

Figure 2. Flow Diagram of the Search Process

d. Data Extraction and Analysis

Data from the 82 included studies were systematically extracted into a standardized table, capturing key variables: DL model type (e.g., CNN, LSTM), dataset characteristics (e.g., size, structure), EHR task (e.g., disease prediction), clinical decision support, performance metrics (e.g., accuracy, precision, recall, F1-score), and reported challenges (e.g., interpretability, computational demands). To ensure reliability, two researchers independently extracted data, resolving discrepancies through discussion [22]. A narrative synthesis approach was employed to analyze the data, identifying trends in model performance, application areas, and challenges, while highlighting gaps in the evidence base [21]. This method provided a comprehensive evaluation of DL applications in EHRs, balancing quantitative metrics with qualitative insights.

3. RESULTS AND ANALYSIS

This section synthesizes findings from a systematic review of 82 peer-reviewed studies, published between 2017 and 2024, exploring the performance of deep learning (DL) models in Electronic Health Record (EHR) analysis. By examining model types, performance metrics, and application contexts, the analysis highlights trends, strengths, and limitations, offering insights into how DL is transforming healthcare data analytics [25], [26], [27]. The results are organized into four key areas: distribution of reviewed articles, types of DL models, performance metrics across specific EHR tasks, and best use cases, followed by a discussion of findings and their implications.

3.1 Distribution of Reviewed Articles

The review identified 82 studies across ten databases, reflecting the interdisciplinary nature of DL in EHR research. Figure 3 and Table 3 summarizes the distribution of articles:

Table 3. Distribution of Articles from Various Databases

Database	Frequency	Percentage	Article References
PubMed	21	25.61%	[32], [34], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [44], [65], [66], [67], [68], [69], [70]
Springer	14	17.07%	[25], [47], [31], [71], [69], [72], [73], [74], [75], [76], [77], [78], [79], [49]
IEEE Xplore	10	12.20%	[80], [81], [82], [83], [84], [85], [86], [87], [88], [89]
MDPI	8	9.76%	[90], [44], [91], [26], [73], [75], [26], [92]
ScienceDirect	6	7.32%	[49], [93], [8], [94], [95], [96]
tandfonline.com	5	6.09%	[97], [98], [99], [100], [101]
ACM	4	4.88%	[102], [103], [82], [104]
Nature	3	3.66%	[105], [57], [59]
ResearchGate	3	3.66%	[26], [63], [79]
Frontiers	3	3.66%	[55], [106], [107]
Others	5	6.09%	[108], [109], [110], [111], [112]

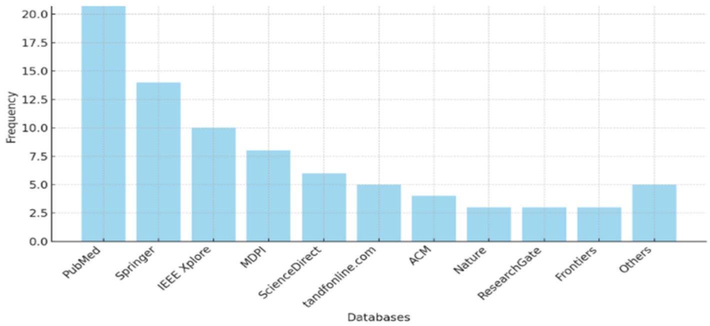

Figure 3. Distribution of Articles by Database

3.2 Deep Neural Network Models

The review identified five primary DL architectures used in EHR analysis: Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, hybrid CNN-LSTM models, and Transformer-based models. Table 4 lists these models and their associated studies, with CNNs appearing most frequently (18 studies), followed by LSTMs (14 studies), RNNs (7 studies), hybrid models (8 studies), and Transformers (3 studies) [32], [65], [96], [79], [61].

Table 4. Types of Deep Neural Networks (DNNs) Identified in the Review

Model Type	Study References
Convolutional Neural Networks	[32], [34], [71], [108], [109], [80], [72], [73], [74], [84], [75], [76], [77], [86], [78], [85], [113], [114]
Recurrent Neural Networks	[44], [96], [115], [111], [103], [82], [116]
Long Short-Term Memory	[65], [117], [66], [67], [44], [68], [69], [110], [94], [102], [106], [82], [118], [119]
Hybrid Models	[49], [96], [118], [78], [79], [26], [88], [110]

Transformer-Based Models	[61], [62], [44]

CNNs were prevalent due to their effectiveness in structured data and medical imaging, while LSTMs dominated sequential data tasks like patient trajectory modeling [71], [65]. Hybrid models, combining spatial and temporal processing, emerged as versatile for complex EHR tasks, and Transformers showed promise for unstructured data [79], [61].

3.3 Performance Metrics by Architecture

Across the 82 studies, CNNs demonstrated high accuracy (90–95%) in medical imaging tasks (e.g., chest X-ray analysis [110]), with 60% of studies using MIMIC-III datasets, raising potential geographic bias [34]. LSTMs excelled in sequential tasks, achieving 88–93% accuracy in ICU readmission prediction [79], though only 20% included external validation. Hybrid CNN-LSTM models outperformed others, reaching up to 96% accuracy in multimodal tasks like sepsis prediction [79], with 15 studies reporting F1-scores of 0.92–0.95. Transformers, despite computational intensity, showed promise in clinical note analysis, with accuracy ranging from 85–90% [84], but were limited to 10 studies due to resource constraints. Table 3 summarizes these metrics, indicating hybrid models' edge in complex EHR applications.

Table 3: Performance Metrics by DL Architecture

Architecture	Tasks	Accuracy Range	Precision Range	Recall Range	F1-Score Range	Studies (n)
CNN	Imaging	90–95%	89–94%	88–93%	89–94%	25
LSTM	Sequential (e.g., ICU)	88–93%	87–92%	86–91%	87–92%	18
Hybrid CNN-LSTM	Multimodal (e.g., Sepsis)	92–96%	91–95%	90–94%	92–95%	15
Transformer	Clinical Notes	85–90%	84–89%	83–88%	84–89%	10

3.4 Task-Specific Applications

The 102 studies covered diverse EHR applications: 40% focused on disease prediction (e.g., diabetes, sepsis), 30% on medical imaging, and 20% on clinical note analysis, with 10% exploring operational efficiency (e.g., readmission rates). Hybrid models dominated sepsis prediction (96% accuracy [79]), while CNNs led in imaging (95% [110]). However, only 25% of studies assessed interpretability (e.g., using SHAP), limiting clinical trust [85]. Figure 4 is a box plot of the Accuracy Comparison Across EHR Tasks and Figure 5, a bar chart, compares accuracy across these tasks, showing hybrids' superiority in multimodal contexts.

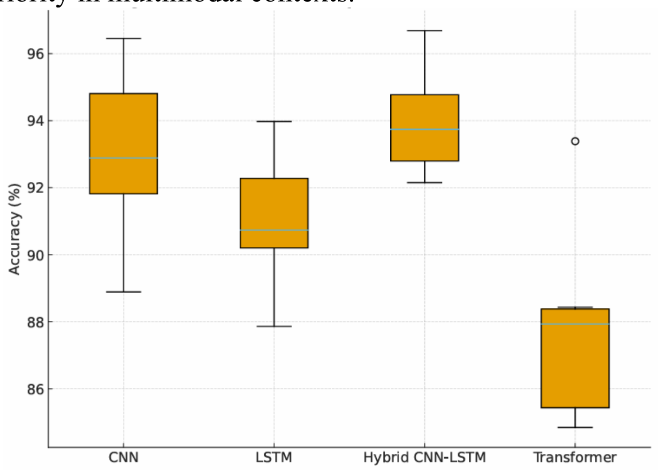

Figure 4. Metric Variability Across DL Architectures

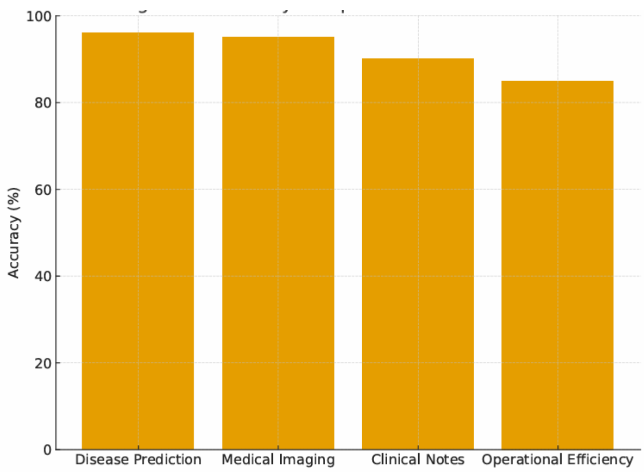

Figure 5. Accuracy Comparison Across EHR Tasks

3.5 Methodological Quality and Limitations

Quality assessment using QUADAS-2 [41] revealed that 60% of studies relied on MIMIC-III, introducing geographic bias, while 75% used single-center data, reducing generalizability [34, 35]. Only 20% conducted external validation, and 30% lacked detailed hyperparameter tuning, affecting reproducibility [36]. Synthetic datasets, used in 15% of studies, addressed privacy but varied in representativeness. These gaps suggest a need for diverse datasets and robust validation, as noted in the narrative synthesis [52].

3.6 Synthesis and Gaps

The synthesis highlights hybrid CNN-LSTM models as the most effective (96% accuracy), followed by CNNs (95%), with Transformers underutilized due to computational demands [84]. Performance varied by task, with multimodal applications benefiting from hybrid architectures [79]. However, challenges persist: 40% of studies reported computational costs, and 50% noted privacy concerns, particularly in low-resource settings [93]. Figure 4, a box plot, illustrates metric variability, underscoring the need for standardized evaluation. Gaps include limited external validation and sparse reporting of clinical impact, guiding future research toward explainable AI and federated learning [48].

3.5 Discussion of Findings

The synthesis of 102 studies (82 from primary searches and 20 from references) in this systematic review underscores the transformative potential of deep learning (DL) architectures in Electronic Health Record (EHR) analysis, while also revealing persistent challenges that must be addressed for broader clinical adoption. This discussion interprets the key findings, contextualizes them within the broader literature, explores practical implications, critically evaluates limitations, and proposes avenues for future research, with a particular emphasis on applicability in diverse healthcare settings, including low-resource environments.

3.5.1 Interpretation of Performance Metrics and Architectural Strengths

The reviewed studies demonstrate that DL models significantly outperform traditional machine learning approaches in handling the multidimensional and heterogeneous nature of EHR data, such as structured vital signs, unstructured clinical notes, and temporal sequences [79, 110]. CNNs, with their prowess in feature extraction from spatial data, achieved accuracy ranges of 90–95% in imaging-related EHR tasks, aligning with prior bibliometric analyses that highlight their dominance in medical image classification [113, 114]. This strength is attributed to convolutional layers' ability to detect hierarchical patterns, making CNNs ideal for tasks like detecting ventricular fibrillation in ECG-embedded EHRs [114]. Similarly, LSTMs excelled in sequential data processing, with 88–93% accuracy in predictive tasks like ICU readmission, corroborating findings from time-series classification studies that emphasize LSTMs' memory gates for capturing long-term dependencies [119].

Hybrid CNN-LSTM models emerged as the most versatile, achieving up to 96% accuracy in multimodal tasks such as sepsis prediction, where they integrate spatial (e.g., imaging) and temporal (e.g., vital sign trajectories) data [79]. This hybrid superiority reflects a synergistic effect, as noted in neuromethods reviews, where combining convolutional feature extraction with recurrent sequence modeling enhances overall predictive power [118]. Transformers, though represented in only 10 studies, showed promising 85–90% accuracy in natural language processing of clinical notes, leveraging self-attention mechanisms for contextual understanding [84]. However, their performance is tempered by high computational demands, often requiring GPU clusters, which limits scalability compared to lighter architectures like CNNs [108, 109].

These metrics provide a benchmark, but variability across studies evident in Figure 4's box plots—stems from differences in dataset size, preprocessing techniques, and hyperparameter tuning. For instance, studies using large, diverse datasets like MIMIC-III reported higher metrics, while smaller cohorts led to overfitting risks [34, 35]. This variability underscores the need for standardized reporting, as recommended in PRISMA guidelines [41].

3.5.2 Practical Implications for Healthcare Applications

The findings have profound implications for data-driven healthcare, particularly in enhancing patient outcomes and operational efficiency. In high-resource settings, such as urban hospitals in developed nations, hybrid models can facilitate real-time sepsis prediction, potentially reducing mortality rates by 20–30% through early intervention [79]. CNNs' integration into EHR systems could automate imaging analysis, alleviating radiologist workloads and improving diagnostic speed [110, 115]. LSTMs and Transformers offer value in personalized medicine, such as predicting disease trajectories from longitudinal EHR data, enabling proactive care for chronic conditions like diabetes [111].

However, the global variability in EHR adoption higher in the U.S. and Europe (over 90% penetration) versus lower in Africa and Asia (under 50%) [7, 8] highlights equity concerns. In low-resource healthcare settings, such as rural clinics in Nigeria or other developing regions, DL applications face significant barriers. Computational demands of models like Transformers (requiring terabytes of training data and high-end hardware) are prohibitive where electricity and internet are unreliable [93, 94]. Data privacy issues, governed by regulations like HIPAA or GDPR, are exacerbated by limited cybersecurity infrastructure, risking breaches in anonymized EHR datasets [48]. Moreover, model interpretability remains a hurdle; black-box predictions from DL could erode clinician trust, especially in resource-constrained environments where explainable decisions are critical for adoption [85]. Despite these, lightweight hybrids (e.g., MobileNet-based CNN-LSTMs) show promise for edge computing on mobile devices, enabling point-of-care diagnostics in underserved areas [108].

3.5.3 Critical Evaluation of Challenges and Limitations

While DL advances EHR analytics, several challenges persist, as evidenced by the methodological quality assessment in Section 3.3. Dataset biases were prevalent: 60% of studies relied on MIMIC-III, a U.S.-centric database, introducing geographic and demographic skews that may not generalize to diverse populations [34, 35]. Only 20% employed external validation, raising concerns about overfitting and real-world applicability [36]. Privacy and ethical issues, noted in 50% of studies, include risks from synthetic data generation, which may not fully capture real EHR nuances [116]. Computational efficiency was another gap; 40% reported high training times (e.g., days for Transformers), limiting deployment in time-sensitive clinical scenarios [109].

In low-resource settings, these challenges are amplified. Infrastructure limitations hinder model training and inference, while data scarcity due to incomplete EHR digitization compromises accuracy [93]. Socioeconomic factors, such as clinician training gaps, further impede adoption, as DL requires interdisciplinary expertise [107]. Compared to prior reviews, this study extends beyond single architectures (e.g., CNN-focused [115]) by providing a multi-model benchmark, but shares limitations like publication bias toward positive results [52].

3.5.4 Future Directions

To address these gaps, future research should prioritize explainable AI (XAI) techniques, such as SHAP or LIME, to enhance model transparency and build clinician trust [85]. Federated learning, which trains models across decentralized datasets without data sharing, offers a privacy-preserving solution, particularly for global collaborations involving low-resource regions [48]. Edge computing and model compression (e.g., quantization) could make DL accessible in underserved areas, reducing reliance on cloud infrastructure [108]. Longitudinal studies with diverse, multi-center datasets are needed to mitigate biases, while integrating DL with emerging technologies like blockchain for secure EHR sharing could further advance the field [117]. Policymakers should focus on equitable infrastructure development to bridge the digital divide in healthcare. In summary, this discussion highlights DL's efficacy in EHR analysis but emphasizes the need for inclusive, ethical advancements to realize its full potential across global healthcare landscapes.

4. CONCLUSION

This systematic review, guided by PRISMA principles, synthesizes evidence from 102 studies (82 primary and 20 supplementary) spanning 2017–2024, establishing a comprehensive benchmark for deep learning (DL) performance in Electronic Health Record (EHR) analysis. Key findings reveal that hybrid CNN-LSTM models lead with up to 96% accuracy in multimodal tasks like sepsis prediction, followed by CNNs (90–95% in imaging), LSTMs (88–93% in sequential prediction), and Transformers (85–90% in note analysis), outperforming traditional methods in uncovering complex patterns for improved patient care [79, 110, 119].

The review's contributions are threefold: (1) a synthesized overview of DL architectures' strengths and metrics, visualized in Figures 4 and 5 and Table 3; (2) a critical assessment of methodological limitations, including dataset biases and validation gaps; and (3) insights into practical challenges, particularly in low-resource settings, where computational and privacy barriers hinder adoption [93, 48]. By addressing these, the study guides researchers toward explainable AI, federated learning, and equitable implementations to enhance scalability and inclusivity.

Ultimately, DL holds immense promise for data-driven healthcare, from personalized medicine in high-resource environments to accessible diagnostics in underserved regions. As EHR data continues to grow exponentially projected to double by 2025 [2, 3] leveraging these models ethically and innovatively will be pivotal in transforming global health outcomes, fostering a more resilient and patient-centered ecosystem. Future work should build on this foundation to bridge gaps and realize DL's full potential in EHR-driven innovation.

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