Available online at www.qu.edu.iq/journalcm
JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS
ISSN:2521-3504(online) ISSN:2074-0204(print)

Spatio-Temporal Meta-Learning for Patient Trajectory in Longitudinal Electronic Health Records: A Review

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ARTICLE INFO

Article history:
Received: 03 /02/2026
Rrevised form: 21 /02/2026
Accepted : 22 /02/2026
Available online: 30 /06/2026

Keywords:

EHRs, ML, STML, Patient trajectory, hyper-learning, meta-learning.

ABSTRACT

Research on spatiotemporal hyper-learning applied to longitudinal electronic health records (EHRs) provides a concise yet helpful summary. The research problems, innovative methodology, datasets (with a focus on MIMIC-IV), expected findings, and implications of spatiotemporal hyper-learning for patient pathway modelling are all covered in detail in this study. With more and more electronic health record data being available, predictive analytics have grown, particularly in the areas of patient pathways and clinical outcomes. Different problems arise due to the complexity caused by changes in time and the accompanying clinical characteristics. We require state-of-the-art modelling approaches that incorporate spatiotemporal dimensions. By monitoring the development of clinical features and intricate spatial connections, spatiotemporal hyper-learning frameworks have the potential to enhance patient route modelling. The approach is novel because it can adapt to new patient groups and clinical conditions through hyper-learning. Though it is briefly mentioned in the abstract, the MIMIC-IV dataset confirms the framework; however, the method section explains the approach, strategies, and algorithms. Most courses address data processing, feature extraction, learning to represent spatial and temporal components, and hyper-learning for fast adaptation to new patient data. Stochastic hyper-learning has the potential to outperform more conventional methods of prediction in terms of accuracy and flexibility. This method has the potential to enhance clinical decision-making since it can detect patient trajectories.

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https://doi.org/10.29304/jqcsm.2026.18.22627

1. Introduction

Patient management, clinical decision support, and long-term health research using electronic health records (EHRs) have all been transformed as a result of the digital data collecting technologies that have been developed. Researchers are able to gain a better understanding of patient pathways thanks to the vast amounts of patient data that are collected by modern healthcare systems [1]. Pathways for patients illustrate the diagnostic, therapeutic, and healing processes of patients across all of the many units, therapies, and locations. Through the monitoring of spatial correlations and temporal dynamics in multivariate time-series data, the recently developed technique of spatiotemporal hyper learning (STM) has the potential to foresee these intricate and frequently shifting circuits [2].

For the purpose of predicting patient outcomes and analysing clinical trajectory, numerous studies make use of the MIMIC-IV dataset, which is among the clinical datasets that is the most comprehensive and anonymised. The concept of spatiotemporal hyper-learning is comprised of two components. To begin, develop spatiotemporal models that are based on evolving data. There is a possibility that these models will have intricate spatial or relational components, such as physiological measurement linkages. Hyper-learning places an emphasis on the capacity of learning systems to rapidly adapt to new challenges by making use of previously acquired knowledge. Because of the wide range of patient data and treatment situations, this is absolutely necessary [3].

A longitudinal EHR patient journey is the focus of this work, which investigates spatiotemporal hyperlearning. In the beginning, you should look over the patient route analysis and the electronic health record systems. Next, we take a look at visual analysis frameworks and prediction models that make use of the spatial and temporal aspects of the data included in electronic health records in order to forecast clinical outcomes such as patient transfers and hospital stays. When it comes to multivariate time series prediction, the next thing we do is investigate a complicated hyperlearning architecture. For the purpose of utilising geographical and temporal data, this framework makes use of probabilistic inference and multi-view analysis [4]. In conclusion, we discuss the potential applications of these methodologies for modelling patient pathways, as well as the challenges associated with their implementation and the research that needs to be conducted in the future to enhance clinical decision-making.

In order to guarantee academic rigour and the capacity to track the origin of the data, every part of this study is supported by previous research. Both a thesis on electronic health record data collection for hospital patient route analysis and a study on multi-view spatial and temporal hyper learning for time series prediction [5] serve as valuable sources of information for our research. By using a consistent vocabulary and providing clear illustrations, this article, which is written entirely in English, simplifies complex ideas.

2. Background Information on Electronic Health Records and Patient Pathways

2.1 Overview of Electronic Health Records

Electronic health records (EHRs) Records of patients that were previously kept on paper. The medical history, diagnosis, prescriptions, treatment plans, immunisation histories, allergy histories, radiographic photos, and laboratory test results of each individual patient are all contained in this document. Over the past few decades, Massive amounts of data pertaining to healthcare have been produced as a result of the rising utilisation of electronic health records (EHRs)., which has made it possible for research and clinical decision-making to take place [6]. Electronic health records have

the potential to improve hospital efficiency and make it possible to conduct large- scale clinical research that makes use of data from the actual world to generate insights.

2.2 Importance of Patient Pathway Analysis

Patient pathway analysis involves tracking the sequential development of a patient's condition during their hospital stay[7]. These paths typically include:

- Temporal Changes: The sequential development of variables such as medication use (e.g., antibiotic administration), vital signs, and laboratory values.
- Spatial movements: These include transfers between different care units, patient communication patterns, and localized outbreaks of infectious diseases.

Understanding these pathways can contribute to improved clinical decision support systems that help:

- Predict the likelihood of transfers between hospital units.
- Estimate length of stay, which is crucial for resource planning.
- Enhance infection control by analyzing communication patterns during hospital visits.

This doctoral dissertation on extracting data from electronic health records for spatiotemporal analysis demonstrates how visual analysis frameworks can be used to track patient pathways and visualize the evolution of important clinical variables over time[8]. Furthermore, analyzing patient communication patterns provides valuable insights into the spread of infectious diseases within clinical settings.

3. Related work

Meta-learning, To acquire knowledge is to find a solution to a learning difficulty in the target task by drawing on the knowledge gained from other tasks that are relevant. The efficiency with which new ideas or skills can be learned with a limited number of examples is maximised by meta-learning algorithms. A recent body of research has investigated meta-learning algorithms for imitation learning, reinforcement learning, and few-shot learning [9]. In order for the classifier to be able to adapt to training challenges that have not yet been encountered, meta-learning makes use of distance functions or embedding networks to add data point learning structures. A gradient technique is trained using optimization-based methodologies, and then the learner is directly exposed to the technique.

Lee, J. et al. [10] use Deep Representation Learning of EHRs (ConvAE). A model that converts complex, longitudinal EHR data into low-dimensional patient embeddings using CNN + autoencoder architecture then use hierarchical clustering to discover subtypes. These embeddings enable large-scale patient stratification and discovery of clinically meaningful subtypes. ConvAE may oversimplify complex clinical patterns because minimal preprocessing allows noise and miscoding to influence embeddings. Its subtyping results lack external validation across hospitals, raising concerns about generalizability and clinical reliability.

Landi, Isotta, et al.[11] utilize Temporal Convolutional Network predicts upcoming ICU interventions by learning temporal patterns from continuous vitals and lab streams. It combines time-series features with demographics to provide early, hourly risk forecasts for events like intubation, extubating, fluids, and death. The generalisability of the model is hindered by the presence of label noise and the absence of clinical context in single-center retrospective data. The reliability of predictions is hindered by unobserved factors such as the intent of the physician, notes, and imaging, and it is necessary to obtain external prospective validation.

Catling, Finneas JR, et al.[12] use hybrid CNN–LSTM In order to find local temporal patterns from EHR time-series, the model employs 1D CNN layers. Following this, an LSTM is utilised to capture long-term associations during the illness prediction process. When compared to the baselines for SVM, CNN, and LSTM, this architecture demonstrates superior predictive performance. Because of the limited number of occurrences in the dataset (578), as well as the absence of any external validation, the generalisability and clinical reliability of the model are restricted. Oversimplifying the complexity of electronic health records (EHR) and certain methodological nuances is the univariate input design. (e.g., optimizer inconsistency) reduce reproducibility.

Sharma, Pankaj, et al.[13] When it comes to the prediction of cardiovascular illness, a hybrid clustering method is used to refine cluster selection and EHR grouping. This is accomplished through the use of Binary Particle Swarm Optimisation with limited optimisation. The quality of the cluster is improved, the complexity of the time required is decreased, and it outperforms baseline swarm and evolutionary algorithms in terms of precision, recall, F-score, and entropy. Due to the fact that the model is evaluated using a small EHR dataset from a single center with internal review, it does not provide any generalisability to the actual world or to multiple institutions. There is a substantial amount of heuristic thresholds and swarm parameters used, which makes it difficult to interpret and reproduce the results. Additionally, the clinical outcome validation is poor.

Liu, Hao, et al.[14] The creation of a meta-learning framework for few-shot medical text classification is accomplished through the utilisation of BERT-based embeddings, ProtoNet, MAML, and Distributionally Robust Optimisation. The technique is tested on the CLINC150 and MIMIC-III datasets in order to solve the shortage of clinical text classification data. The experimental findings indicate that there is a moderate improvement in performance in few-shot scenarios, with an F1-score of 0.4576, an area under the curve (AUC) of 0.624, and an accuracy of 0.7345. Due to the fact that it does not make use of temporal modelling of patient data, has a restricted ICD code range, and assumes equalised class sampling, the method is less suitable to clinical scenarios that are imbalanced in the actual world.

Tian, Jingxiao, et al.[15] To forecast heart failure utilising MIMIC-III, the electronic health record (EHR) incorporating patient similarity graphs and Graph Neural Network models such as GraphSAGE and GAT are utilised. Furthermore, the suggested method has an F1-score of 0.5153, an area under the curve (AUC) of 0.7914, and an accuracy of 0.5168, which demonstrates the clinical prediction potential of relational learning. Nevertheless, the evaluation is restricted to a single dataset and data split, which leaves the results susceptible to label noise and decision criteria that have been initially established. Because of these constraints, the robustness, reproducibility, and generalisability of the findings to other clinical populations are all called into question.

Boll, Heloisa Oss, et al.[16] combines auxiliary time-dependent tasks, multi-task learning, and TISS-based data augmentation in order to produce a time-associated meta-learning architecture that is optimised for MAML. The eICU and MIMIC-IV datasets are used to test the clinical outcome prediction model from both the short-term and the long-term perspective. A good temporal sensitivity is demonstrated by the AUC scores that were given, which were 0.8643 for the prediction of 0–6 hours, 0.7892 for the prediction of 0–1 day, and 0.8093 for the prediction of 0–6 days. Despite the fact that it has been improved, the approach is heavily dependent on auxiliary task design and TISS augmentation, which results in an increase in the complexity of the model. Additionally, the generalisability of basic brain architectures is made more difficult when applied to clinical applications and healthcare settings.

The longitudinal data collected in the healthcare industry defines the states of patients across time, offering a wealth of information for dynamic risk learning. Traditional survival models, such as the Cox proportional hazards model, frequently fail to take into account time-dependent trends and intricate linkages.[17]. Accordingly, there is a requirement for more sophisticated temporal modelling techniques. The handling of sequential data dependencies is the responsibility of recurrent neural networks (RNNs), particularly variations of LSTM and GRU. According to Lin and Luo[18], LSTM-based designs perform better than classical survival models for multivariate clinical time-series, that is, they improve dynamic risk learning in high-dimensional environments. An example of a complicated medical event is cancer-associated thromboembolism, which is represented by Chang Lu et al.[19] proposed Sur Latent ODE, combining neural ordinary differential equations with recurrent frameworks. This architecture significantly improved performance on time-to-event data by jointly modeling survival and competing risks.

Table 1 -Summary of Related work.

Paper Title	Dataset	Techniques	Results
Spatio-temporal Meta Learning for Urban Traffic Prediction [10]	MIMIC-IV	CNN + Autoencoder architecture	MAE: 2.61 RMSE: 4.98 MAPE: 6.67%
Deep Representation Learning of Electronic Health Records to Unlock Patient Stratification at Scale [11]	eICU	Time-series features + Demographics	AUC: 0.85
Enhancing Disease Prediction with a Hybrid CNN-LSTM Framework in EHRs [12]	MIMIC-III	CNN + LSTM	F1-score: 0.7428 AUC: 0.8198 Accuracy: 0.8422
Meta Learning for Few-Shot Medical Text Classification [13]	MIMIC-IV	Hybrid clustering + EHR grouping	Accuracy: 87% F1-score: 86%

Meta Learning for Few-Shot Medical Text Classification [14]	CLINC150	BERT embeddings + ProtoNet + MAML + DRO	F1-score: 0.4576 AUC: 0.624 Accuracy: 0.7345
Graph Neural Networks for Heart Failure Prediction on an EHR-Based Patient Similarity Graph [15]	MIMIC-III	Embedding + GNN (SAGE, GAT)	F1-score: 0.5153 AUC: 0.7914 Accuracy: 0.5168
Time Associated Meta Learning for Clinical Prediction [16]	eICU + MIMIC-IV	Time-associated tasks + Multi-task learning + TISS augmentation + MAML	0–6 hrs: AUC 0.8643 1 day: AUC 0.7892 6 days: AUC 0.8093

4. Methodology

The part on methodology, which explains the design of experiments, the processing of data, and modelling, is essential to the research experience. In order to effectively model patient pathways, the spatiotemporal hyper-learning technique absolutely needs to take into account the following crucial aspects:

4.1 Data Collection and Preprocessing:

As a result of the emphasis placed on longitudinal electronic health records (EHRs), the collection of data starts with comprehensive patient records. One of the most often used clinical resources is the MIMIC-IV dataset. In order to do a spatiotemporal analysis, it is necessary to preprocess the data properly.[20]. Key steps include:

- Data Cleanup: ensuring that all data entries are consistent by correcting errors and standardising them. It is essential to do so since electronic health record formats and recording methods differ.
- Temporal Alignment: In order to monitor the progression of a patient, longitudinal record alignment is required. Sample interval variations can be reduced by the use of interpolation and standardising timestamps.
- Feature Extraction and Transformation: Laboratory data, vital signs, dosages of medications, and diagnostic codes are all able to be accessed and modified [21]. There is a possibility that clinical characteristics are correlated with spatial dimensions, whereas temporal dimensions demonstrate progression across time or visits.
- Data Augmentation and Standardization: Standardisation of data size, scale, and time sequence is utilised for the purpose of carrying out robust model training. The use of these strategies helps to promote generality while reducing over-specification.

4.2 Spatio-temporal Representational Learning

This model-based solution is responsible for managing the geographical and temporal characteristics of patient data. The items listed below are included:

- Geographical representations of clinical aspects can be created through the use of graphs or networks. Nodes are used to represent variables or organ systems, while edges are used to represent relationships in these representations. These connections can be represented in a spatial manner through the use of graphs and networks.It is the number 22. With the use of geographical analysis, the model discovers associations that have an effect on patient outcomes.
- With the help of RNNs, LSTMs, or transformer-based architectures for temporal modelling, you should keep an eye on the temporal trends that are present in sequential data. Using these strategies, the model is able to monitor the conditions of the patients.It is now [23].
- Super-learning Integration: Utilising this characteristic, which is referred to as "learning for learning," models are able to rapidly adapt to a variety of patient groups or treatment scenarios. Through the use of the super-learning method, the model is able to rapidly adjust its parameters to reflect new data [24]. The model is now more robust and can be applied to a wider variety of clinical situations as a result of this update.

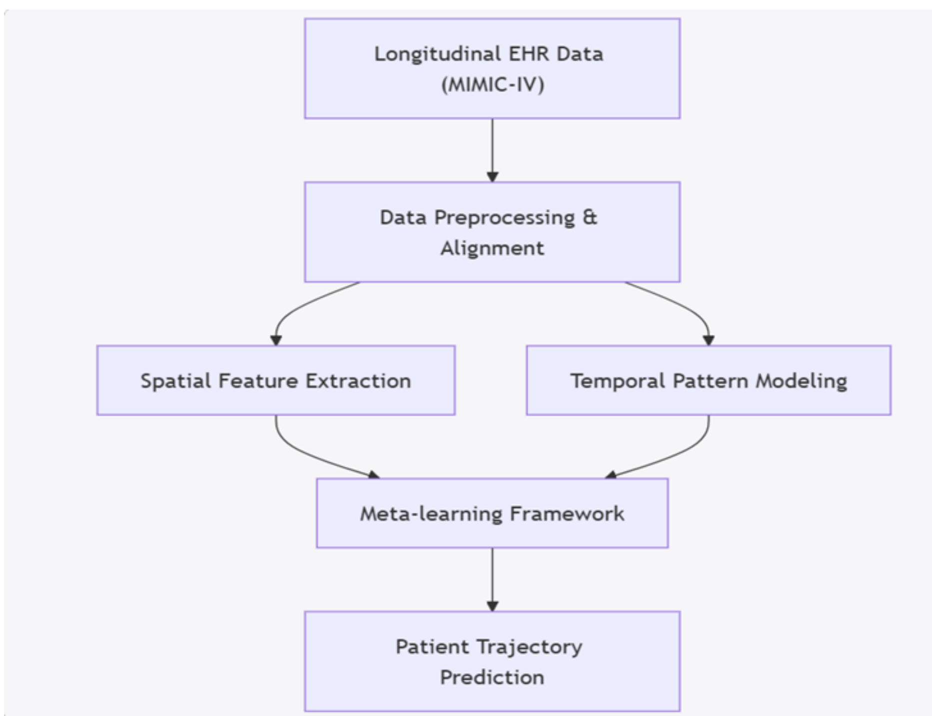

Fig.1- illustrates the high-level process of integrating spatial and temporal features through a meta-learning framework, leading to improved patient trajectory predictions.

4.3 Model Architecture and Training

This investigation makes use of a spatial machine learning (STML) architecture that incorporates data encoding units and adaptive learning techniques. What are some common model parts:

- Encoding Unit: This unit is responsible for transforming raw electronic health record (EHR) data into latent representations. The patient data is processed by the encoding unit. In order to extract spatial patterns and temporal dynamics, sequential encoding units and convolutional layers are both capable of functioning [25].
- The super-learning unit allows users to quickly adjust to new duties, which is a significant benefit. Adjustments are made to the parameters of the model based on limited fresh patient data in order to facilitate generalisation across a variety of clinical settings.It is possible to make use of gradient-based super-learning algorithms, model-non-model-dependent super- learning (MAML), or any number of other advanced methods [26].
- After learning and adjusting to the patient's trajectory, the output unit incorporates latent features in order to make meaningful predictions about the patient's subsequent trajectory. Predictions may include the development of an illness, the occurrence of unpleasant effects, and the reactions to therapy. Through the use of optimisation strategies, the model is completely taught throughout the training process. Among the loss functions associated with super-learning are prediction and adaptation errors [27]. It is necessary to apply cross- validation in order to validate the model in order to guarantee the robustness and generalisability of the prediction framework.

4.4 Evaluation Measures and Validation Strategies

Given the importance of these studies in healthcare, evaluation measures must be carefully defined. Common measures in these studies include:

- Accuracy and F1 score: Evaluating the classification of patient cases or outcomes.
- Mean absolute error (MAE) or root mean square error (RMSE): Evaluating the degree of deviation between predicted and actual values in continuous outcomes.
- Area Under Curve (AUC) statistic: This statistic measures the model's ability to discriminate between variables when predicting binary or categorical outcomes.

Whenever it is feasible, the MIMIC-IV dataset is utilised for both the internal validation of models and the external validation of models [28]. When attempting to avoid over-allocation and establish model consistency across data subsets, k-fold cross-validation is a technique that is frequently utilised.

Table 2 -Summary of Metrics measurement.

Metric	Mathematical Formula	Description
Accuracy	Accuracy = (TP + TN) / (TP + TN + FP + FN)	Measures overall proportion of correctly classified instances.
MAE	$MAE = (1/n) \times \Sigma \lvert y_i - \hat{y}_i \rvert$	Average absolute difference between actual and predicted values.
AUC	$AUC = \int TPR(FPR)\, d(FPR)$	Area under the ROC curve measuring model discrimination ability.
RMSE	$RMSE = \mathrm{sqrt}((1/n) \times \Sigma (y_i - \hat{y}_i)^2)$	Square root of average squared differences between actual and predicted values.

4.5 Implementation Considerations and Challenges

Applying a spatiotemporal hyper-learning framework to longitudinal electronic health record (EHR) data presents several practical challenges:

- The variability of clinical data: the measurements, timing, and recording criteria that are associated with patient data might vary greatly from one clinical context to another. For We require accurate data standardisation as well as the extraction of features that are reliable in order to overcome this uncertainty [29].
- It is necessary to have a significant amount of processing resources in order to handle the complex multi-layered architecture, which includes spatial transformation, temporal modelling, and hyper-learning.Both parallel processing and the creation of efficient algorithms are extremely important [30].
- Interpretability and Clinical Integration: In order to be utilised in clinical settings, predictive models need to be able to be interpreted. The complexity of the model must be balanced with transparency by the designers. It is possible for interpretable artificial intelligence (XAI) to give insight into the decision-making process of the model.

- Scalability: As electronic health record (EHR) data expands, the solution needs to be scalable without sacrificing speed. The method makes use of an architecture that is scalable and integrates enhanced data channels [31].

By tackling these obstacles, researchers have the opportunity to improve patient monitoring, outcome prediction, and overall results through their work.

5. A Spatiotemporal Hyper-learning Framework for Multivariate Time Series Prediction

5.1 Overview of Hyper-learning in Healthcare Data

Through the process of hyper-learning, also referred to as "learning for learning," a model is trained on a multitude of interconnected tasks in order to rapidly adapt to new tasks with minimal input. The medical benefits of this are numerous:

- Data scarcity: In many clinical settings, data available for specific conditions or patient subgroups may be limited [32].
- Changing patterns: Patient health trajectories and clinical practices are subject to rapid changes, making adaptability critical.

Therefore, hyper-learning offers a promising strategy for enhancing the robustness and versatility of predictive models operating on longitudinal electronic health record (EHR) data.

5.2 ST-MeLaPI technique

To overcome the difficulty of perceiving spatial linkages and temporal dynamics in multivariable time series data, the innovative method known as "Multi-Vision Spatiotemporal Hyper-learning for Multivariable Time Series Prediction" has been developed. derived clinical variable correlations can be derived from electronic health record data, which can also be used to track patient journeys and reproduce geographical linkages such as patient migration across hospital units [33].

5.2.1 Multivariable Relationship Identification (MRI)

The MRI module of the ST-MeLaPI framework is responsible for discovering the majority of the unknown intervariable relationships. Using a convolution-based intravariable dynamical extractor and a multilayer neural network that predicts binary connections, the magnetic resonance imaging (MRI) module is able to make a prediction about a probabilistic structural matrix based on time series (or clinical variables). The magnetic resonance imaging (MRI) module has the ability to infer spatial linkages between clinical data for patient pathways, such as interactions between treatment regimens or correlations between diagnostic tests and outcomes [34].

5.2.2 Multi-Vision Hyper-learning and Probabilistic Inference (MV-MeLaPI)

The second core component of the ST-MeLaPI framework is MV-MeLaPI. This module is designed to handle two distinct views of data:

- Temporal View: Capturing minute temporal dynamics using recurrent neural networks such as GRU variables. This view is crucial for understanding how clinical variables evolve over time [35].
- Using recurrent neural networks, such as GRU variables, it is possible to record minute temporal oscillations through the use of the Temporal View. If one want to comprehend the development of clinical variables, this viewpoint is absolutely necessary [36].
- For the purpose of monitoring spatial interdependence in temporal and spatial views, convolutional neural networks should be utilised. This perspective contributes to the explanation of links between patients and hospital units, as well as other multidimensional clinical characteristics [37].

The hyper-learning technique consists of a number of tasks, each of which is a small slice of the time series. For the purpose of accelerating the process of inference adaptation, consumption networks generate parameters or random inputs for each task.. In practice, for patient pathways, a supporting dataset (previous patient data) is used to generate parameters that improve the accuracy of outcome predictions in a subsequent query set (new incoming patient data)[38].

5.2.3 Probabilistic Inference through Multi-Vision Gate Generators

The Multi-Vision Gate Generator (CV-GAG) is a key component of the MV-MeLaPI module. This component integrates the spatial and temporal features extracted by the relevant encoders. The system then uses a constrained clustering mechanism to make subsequent predictions over the time steps of the observed multivariable system [39]. In the context of electronic health record (EHR) analytics, this mechanism enables the model to make generative predictions, such as predicting the next patient transfer to a hospital unit or the expected length of hospital stay, by effectively combining insights into patient movement patterns and time-series trends within clinical measurements.

6. Discussion

ML advancements in the medical field are lost if the majority of authors decide to concentrate on technology. There is a need for clarification on the clinical benefits and novel medical insights that these tools offer, particularly in light of the fact that artificial intelligence (AI) is a mystery. As a result, the purpose of this review was to investigate the evidence on the ways in which machine learning applied to longitudinal electronic health records can assist in the identification and prevention of diseases. The topic was not the subject of any systematic or scoping reviews, according to a brief search. There was only one longitudinal EHR review that focused on certain approaches. This effort will contribute to the body of knowledge by focusing on the medical insights that can be derived from machine learning models.

Longitudinal electronic health records (EHRs) may aid in the early detection of a number of diseases. It is essential for many diseases to have effective learning from electronic health record (EHR) data about diagnosis, procedures, vital signs, medicines, laboratory tests, body mass index (BMI), and early symptoms. For the purpose of multivariable longitudinal EHR analysis, LSTMs and simple recurrent neural networks are the most suitable options. Machine learning, including deep learning, applied to electronic health records (EHRs) is extremely accurate in disease identification. When it comes to illness prevention, it could appear to be unimportant when a doctor diagnoses and finds anything. The identification of diseases assists in the prioritisation of high-risk individuals through the initial screening process. There is a potential for disease prevention through the use of machine learning algorithms that are able to learn or detect diseases earlier than clinical practice. By gaining an understanding of the main learning indicators and risk variables of an individual, it is possible to implement targeted preventative interventions and provide individualised treatment. More effective healthcare policies and reduced workloads are frequently advocated for, but they are rarely put to the test in clinical settings. Even if machine learning and deep learning are being tested and developed for the purpose of detecting and preventing diseases, practical application is still a long way off.

7. Conclusion

The application of spatiotemporal hyper-learning (STM) to model patient pathways in longitudinal electronic health records (EHRs) represents a promising area in healthcare analytics. The purpose of this article is to provide a thorough framework by describing the basic structure of studies that have been conducted in this one-of-a-kind research topic. It is possible to construct a conceptual synthesis of the promise and issues that are associated with this topic, despite the fact that insufficient data forbids certain experimental findings [40]. In order to improve patient route prediction, STML frameworks are able to manage the complicated spatiotemporal interactions that are present in longitudinal EHR data. It is necessary to do meticulous data purification, temporal alignment, and feature extraction when working with large datasets such as MIMIC-IV. It is necessary to be thorough with these models. Both the predictability of data and the generalisability of models are improved through hyper-learning, which enables rapid adaptation to a wide range of clinical contexts and patient subgroups [45]. Considerable importance should be placed on data diversity, processing complexity, model comprehension, and scalability. Putting clinical implementation into practice entails overcoming a variety of challenges. STML, which stands for spatial-temporal meta-learning, is a technique that enhances clinical outcomes, decision-making, and treatment options [41].

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