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Spatio-Temporal Data Analysis using Deep Learning

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Abstract - *This survey aims to present a thorough overview of the various spatio-temporal data analysis applications of deep learning techniques. The study examines the widely used applications of spatiotemporal data analysis, including transportation, social media events, environmental concerns, human mobility, action recognition, and other related areas. Convolutional Neural Networks, Recurrent Neural Networks, Graph Convolutional Networks, and other neural network architectures are just a few examples of the deep learning algorithms and neural network architectures we discuss in this article for the various spatio-temporal data domains listed above.*

Key Words: Deep Learning, Spatio-Temporal, Neural Network, Metrics, Network Architecture

1.INTRODUCTION

Spatio-temporal data analytics is an interdisciplinary field that deals with the analysis and modelling of data that has both spatial and temporal characteristics. This type of data is commonly generated in various domains such as environmental sciences, geography, transportation, and urban planning, among others. Deep learning, a subset of machine learning, has received a lot of attention lately because of its ability to handle large quantities of complex and multidimensional data. In particular, deep learning has shown to be highly effective in handling spatial-temporal data. The following are some benefits of using Deep Learning models for Spatio Temporal data analysis over more conventional techniques[1]:

Learning hierarchical feature representations automatically: Deep Learning models can learn these representations automatically from the underlying spatiotemporal data.

Effective function approximation capability: If Deep Learning models have enough layers and neurons, they can fit any curve and approximate any complex non-linear function.

Perform better with big data: Conventional machine learning techniques, such as Support Vector Machines and decision trees, typically outperform big data alternatives on smaller datasets before reaching a plateau. When more data is added, deep learning models' performance may continue to improve.

Types of Spatio-Temporal Data were identified by Wang et al. in 2022:

1. Event Data: Discrete events that occur in specific locations at specific times make up event data. An event's type, place of occurrence, and time of occurrence can all be used to define it in general terms.

2. Trajectory Data: Typically, location sensors installed on moving objects provide trajectory data. The sensors transmit and record the object's locations over time at regular intervals.

3. Point Reference Data: A collection of moving reference points scattered over a specific area and time period is used to create these measurements.

4. Video Data: A video (sequence of images) can be categorized as spatio-temporal data type. Neighboring pixels typically share similar RGB values in the spatial domain, exhibiting strong spatial correlations. Succeeding frames exhibit significant temporal dependence in the temporal domain.

The highly complex, substantial, and quickly expanding Spatio-Temporal data, however, continue to present problems. Some of the challenges include the development of interpretable models, and fusion of multi-modal spatio-temporal datasets[1]. We categorize surveyed research papers with respect to their domain, such as Transportation, Environment etc. For each category, we put forth the problem solved by the referenced literature, it's methodology, and results in a concise manner. We have followed a thematic and chronological method for presenting our survey.

2. LITERATURE REVIEW

2.1 Transportation

Zhou et al., 2022 focuses on the challenge of modelling the intrinsic correlation of the ST features that were extracted by the convolutional network apart from the ST aggregation in traffic data, as predictions made as a result of this may have biases that affect subsequent transportation planning decisions. As a remedy, they proposed FASTNN (Filter Attention-based Spatio- Temporal Neural Network). First, the network used residual units to prevent network deterioration and from three categories of traffic flow over time, extracted global Spatio-Temporal dependencies. Filter spatial attention module's development, which quantified the Spatio-Temporal aggregation of the features, allowed spatial weights to be dynamically adjusted. They also developed a small module known as the MFRM (Matrix Factorization Resample Module) to simulate the features' built-in correlation and redundancy. It spontaneously picked up on the inherent correlation of features to enhance the model's attention to information-rich features. Matrix factorization was used to cut down on redundant data between different features[2].

Table -1: REVIEW OF SPATIO-TEMPORAL DATA ANALYSIS IN TRANSPORTATION

Reference	DL Model	Result
Zhou et al., 2022	FAST NN	Least RMSE wrt TaxiBJ. Least RMSE and MAE wrt BikeNYC.
Parsa et al., 2019	LSTM &GRU	GRU better than LSTMwith 95.9% accuracy.
Yu et al.,2018	STGCN	Outperforms baseline models (HA,LSVR, ARIMA)
Ke et al.,2017	FCL-Net	RMSE decreased by48.3%

A novel method for traffic forecasting based on AdaSTGNNs (Adaptive Spatio-Temporal Graph Neural Network) is proposed by Ta et al., 2022 . The suggested method is built on a deep learning architecture that is capable of accurately capturing the intricate spatiotemporal dependencies in traffic flow data. A GCNN (Graph Convolutional Neural Network) and an Attention Mechanism make up AdaSTGNN. In the prediction process, the attention mechanism is employed to adaptively weigh the significance of various time steps, while the GCNN is used to encode the spatial dependencies between traffic flow data from various locations. The paper highlights the potential of adaptive spatiotemporal graph neural networks for traffic forecasting[3].

Parsa et al., 2019 conducted research to identify traffic collisions in Chicago, using LSTM and GRUs to analyze the data taken from the Chicago Motorway. GRU model narrowly beat the LSTM model, with a 95.9% Accuracy, a 75% Detection Rate, and a 3.2% False Alarm Rate. The comparison was based on the Illinois Motorway traffic ST data, data on the weather and the level of traffic congestion. The findings showed that both models detect accidents well, but GRU performs just a little bit better. [4]

A deep learning framework called STGCN (Spatio-Temporal Graph Convolutional Network) was presented by Yu et al. 2018, for spatio- temporal dependency modelling. Data from the Beijing Municipal Traffic Commission (BMTC) and the California Department of Transportation (CDT) was used to validate the model, which included Mean Absolute Error, Mean Absolute Percentage Error, and Root Mean Square Error. Historical Average, Linear Support Vector Regression, Auto-Regressive Integrated Moving Average, Feed-Forward Neural Network, Fully Connected LSTM, and Graph Convolutional Gated Recurrent Unit were used as baselines. The findings showed that the suggested framework performed better than all baselines in terms of every evaluation metric[5].

The FCL-Net (Fusion Convolutional Long Short-Term Memory Network) is an innovative Deep Learning method proposed by Ke et al., 2017 to address Spatio-Temporal and extrinsic dependencies. In Hangzhou, China, it was used to predict passenger demand for an on-demand ride service platform, and was confirmed with the help of DiDi ChuXing's data. The FCL-Net outperformed more conventional approaches taking into account the rate of travel, the time of the day, weekday/weekend, and weather (extrinsic factors). It also decreased the RMSE by 48.3%[6].

2.2 Social Media

Boghiu & Gifu, 2020 present a Spatio-Temporal model for detection of events in the domain of social media, with the goal of extracting events of interest from a significant amount of social media data. The authors propose a spatial-temporal model that uses an LSTM network to simulate temporal dependencies in social media data and a CNN to record spatial features. The authors demonstrate that, with an F1-score of 0.76, their proposed spatial-temporal model outperforms a number of baseline models on the event detection task[7].

On tweets pertaining to context of a particular disaster for a location at various points in time, Parimala et al., 2020 performed sentiment analysis. Using the network's generated keywords, the proposed algorithm, Risk Assessment Sentiment Analysis (RASA), categorizes tweets and determines the sentiment score. The model was verified using Support Vector Machine, Naive-Bayes, Maximum Entropy, Logistic Regression, Random Forest, XGBoost, Stochastic Gradient Descent, and CNNs in a 0-1 (binary) class scenario and in three target classes in a multiclass scenario. The results of the experiment made use of the Kaggle dataset "Social media disaster tweets-DFE" and it was found that RASA outperformed all other techniques by an average of

30% in multiclass scenarios and by 1% in binary class scenarios. The algorithm is divided into two sections: event-based sentiment analysis and tweet keyword generation. The tweets' semantic words are produced by an LSTM network in the initial phase and then fed into the second phase as input, where for a given interval and place, the sentiment score of the watchwords is calculated. In order to take preventive action, the topic's sentiment score is calculated and the accuracy is 89.8%, 86.4%, and 88.5%, respectively. At a multiclass scenario, the accuracy reached 70.98%[8].

Table-2 : REVIEW OF SPATIO-TEMPORAL DATA ANALYSIS IN SOCIAL MEDIA

Reference	DL Model	Result
Boghiu & Gifu et al., 2020	LSTM &CNN	F1-Score of0.76
Parimala etal., 2020	RASA	Outperformed baselines by 30% multiclass scenarios and by1% in binary class scenarios.

2.3 Environmental Issues

Betnsen et al., 2023 developed a deep learning architecture to accurately capture the intricate spatiotemporal dependencies in wind speed data. The authors suggest GCN architecture to model the temporal dependencies in the data, combined with a cutting- edge transformer architecture. This paper illustrates the efficacy of a general framework for multiphase Spatio Temporal forecasting, and evaluates and the effectiveness of various Transformer Architectures in forecasting wind speed[9].

Liu et al., 2022 propose a new spatio-temporal Deep Learning model called ST-LSTM-SA utilizing radar echo images, for rainfall prediction (hourly) and rainfall measurements. The authors use a self- attention mechanism to capture the most important features for the prediction task, which outperforms several baseline models with a Root Mean Square Error of 1.72 mm/h[10].

Hu et al., 2022 proposed a new Spatio-Temporal Deep Learning model; Conv1D-LSTM, which uses a Fully Connected Network for extraction of ST correlation features. The study also suggests an approach that uses improved Inverse Distance Weighting (spatial perspective) and an enhanced Auto-Regressive Moving Average model (temporal perspective) to estimate the missing value. In order to make predictions, the model can pick up on long and short term temporal dependencies as well as close- and far-away spatial correlations. The suggested model is better with respect to generalization & prediction[11].

In a case study using Landsat time-series data, Masolele et al., 2021 explore the use of Spatio-Temporal Deep Learning methods to determine land use after deforestation. The authors propose deep learning framework for accurately classifying the land-use changes that occur after deforestation. The authors use a dataset of Landsat time-series data from multiple sites in the tropics, which includes images before and after deforestation. They pre-process the data to remove clouds and atmospheric effects and extract features using a CNN and a LSTM network. They then use a Spatio Temporal Deep Learning model combining the CNN and LSTM to classify the land-use changes that occur after deforestation[12].

Nevavuori et al., 2020 evaluated the viability of Spatio-Temporal deep learning architectures in modelling of crop yield over time & prediction with RGB time series data using time series Unmanned Aerial Vehicle RGB & weather data from 9 fields in Finland. With full length sequences of approximately 219 kilogram/hectare Mean Absolute Error and 5% Mean Absolute Percentage Error, they measured the performance of the 3D-CNN using CNN and LSTM networks as the Spatial & Temporal base architectures. The best shorter length sequence performance using the same model was approximately 293 kilogram/hectare Mean Absolute Error and around 7% Mean Absolute Percentage Error [13].

Maretto et al., 2021 proposed a fully automatic method for mapping deforestation in the Brazilian Amazon in 2020. This method was tested for a region in southeast Pará state that covers almost 1,11,000 km2 and resulted in an accuracy of 95%. Two Spatio Temporal variations of the U-Network Architecture were proposed, one to take into account spatial and temporal contexts, and the other to consider short- term temporal dynamics. The Average Soft Dice score & weighted cross-entropy were used to test these two variations using two different loss functions[14].

Amato et al., 2020 suggested a deep learning approach for predicting environmental data, based on a Deep Neural Network architecture with multiple convolutional layers and recurrent layers. The authors also introduced temporal dropout for preventing overfitting and for improving the abstraction of the model. The suggested model outperforms all baseline models with respect to both prediction accuracy and computational efficiency[15].

Xiao et al., 2019 suggested a Spatio-Temporal Deep Learning model to project the short and medium term Surface Sea Temperature (SST) field in section of the ECS (East China Sea). The data comes from the National Oceanic and Atmospheric Administration's daily Optimum Interpolation Sea Surface Temperature. The model beats the persistence model, SVR, and a pair of LSTM models having different configurations. A rolling prediction scheme was used to accomplish this prediction, which involves using the surface sea temp. field in the projection window for the upcoming 10 days and the time window for 1 day, incorporating it as its most recent component. Results showed improvements of 14.67% in MAPE and 13.4% in RMSE[16].

The LSTM network was proposed by Hu et al., 2019 for the prediction of floods. It combines predictive and prescriptive analytics to accelerate forecasting and offer efficient response management in emergency situations. The ROM-based LSTM network was used to estimate the spatial aggregation of inundations for the first time in flood forecasting. Predictive analytics is used to recognize patterns in historical and current data and extrapolate dependencies between results using historical or projected data. The cause factors are then estimated based on the predicted results at a later time using the previously learned dependencies[17].

Using a novel Macroscopic Cellular Automata model, the Soil Moisture Content was predicted over a maize field in Northwest China, by Song et al., 2016. Comparing the Macroscopic Cellular Automata-Deep Belief Network to the Macroscopic Cellular Automata-Multi-Layer Perceptron, the RMSE was reduced by 18%. The Macroscopic Cellular Automata model is divided into three phases, with the first phase being preparation of input data and the second phase being calibration data and standardized variables. Deep Belief Network and Multi-Layer Perceptron were used as a weight optimization method for the model's learning capability. The results of the models were consistent and lower than the observed Soil Moisture Contents (6.18%)[18].

Table-3: REVIEW OF SPATIO-TEMPORAL DATA ANALYSIS IN ENVIRONMENTAL ISSUES

Reference	DL Model	Result
Hu et al.,2022	Conv1D-LSTM	Better generalization and prediction performance than baselines.
Nevavuori et al., 2020	3D-CNN, LSTM-CNN, & ConvLSTM	219 kilogram/hectare **MAE** &5% **MAPE** using **3D-CNN**
Maretto etal., 2020	Variations of U-Net	95% Accuracy
Xiao et al., 2020	ConvLSTM	Improvements of 14.67% in MAPE and 13.4% in RMSE.
Song et al., 2016	MCA & DBN	18% reductionin RMSE

2.4 Human Mobility

Sighencea et al., 2023 suggested an attention- based Spatio Temporal Graph Neural Network for predicting trajectories of pedestrians. The method has two parts: Temporal GNN and a Spatial GNN (for motion feature extraction) and a time-extrapolator CNN for predicting the trajectories in the graph's temporal dimension properties. Dynamic Spatio-Temporal Graph Convolutional Network predicts more social trajectories and produces better experimental results. The reduced error in the Average Displacement Error metric was 3% when compared to the cutting-edge SR-LSTM-2 solution and 5% when comparing to the CGNS for the SDD dataset[19].

Miao et al., 2019 proposed a novel approach for counting crowd size in surveillance videos using ST- CNN. The ST-CNN model consists of two main components: a spatial CNN that extracts spatial features from individual frames, and a temporal CNN that captures temporal information across frames. The authors highlight the limitations of traditional crowd counting methods, which rely on handcrafted features and are not effective in capturing the complex Spatio-Temporal patterns of crowds. They propose an End to End trainable deep learning architecture which is capable of automatically learning the features and patterns from raw video data. One of the strengths of the suggested approach is its ability to handle varying crowd densities and motion patterns, which can adapt to different crowd scenes and capture the spatiotemporal variations in crowd behavior. It is therefore a viable option for practical uses like crowd control and security[20].

Zhang et al., 2017 suggested an innovative method for projecting crowd flows in an urban setting using ST-ResNets. ST-ResNet architecture captures the spatial correlations among different locations in a city, and consists of multiple residual blocks with convolutional layers and pooling layers. The residual connections between the blocks allow the network to learn the residual features, which can help to alleviate the vanishing gradient problem in deep networks. The authors compare the suggested model with many baseline models, including traditional regression models, neural network models, and spatial models. The model beats the existing baseline models in terms of prediction accuracy and computational efficiency[21].

Table-4: REVIEW OF SPATIO-TEMPORAL DATA ANALYSIS IN HUMAN MOBILITY

Reference	DL Model	Result
Sighencea etal., 2023	D-STGCN (TGNN and SGNN)	3% reductionin ADE wrt ETH-UCY, 5% wrt SDD

Zhang et al., 2017	ST-ResNets	Outperforms baseline models wrt accuracy and efficiency.

2.5 Action Recognition

Nafea et al., 2021 suggested an innovative method to extract features at different resolutions using CNN with different kernel dimensions and Bi-directional LSTM. This method uses the WISDM and UCI datasets, which collect data using accelerometers, sensors, and gyroscopes. The dataset used by UCI was compiled from recordings of 30 people performing various ADL tasks while wearing smartphones mounted on their waists with built-in inertial sensors. The proposed method allowed for a bi-stream deep learning architecture built on CNN and BiLSTM to acquire temporal features and activity recognition was done by fusing the features that were obtained from the two streams. The Accuracy of the CNN-BiLSTM model was approximately 98% and 97%, respectively[22].

Chen et al., 2021 investigates the use of CNNs for action recognition in videos. It explores different CNN architectures and analyzes the spatio-temporal representations learned by them. It also compares the performance of various CNN-based models on several action recognition datasets. The authors experiment with several CNN architectures, including C3D, I3D, Two-Stream ConvNets, and TSN, and find that the I3D model outperforms other models on UCF101 and HMDB51 datasets[23].

Table-5 : REVIEW OF SPATIO-TEMPORAL DATA ANALYSIS IN ACTION RECOGNITION

Reference	DL Model	Result
Nafea et al., 2021	CNN & BiLSTM	The CNN-BiLSTM model's acc.was approx. 98% and 97% (WISDM-UCI)
Chen et al., 2021	Several CNN architectu-res.	I3D model outperforms other modelson UCF101 and HMDB51datasets.

2.6 Healthcare and Energy

TopoMAD is a sequence-to-sequence model used to effectively model the Spatio-Temporal dependence of contaminated data from cloud systems. It uses sliding windows on metrics collected continuously, system topological information, GNN, and LSTM to obtain spatial features. To validate the methodology, run-time performance data from two representative cloud systems were collected. TopoMAD outperforms some cutting-edge techniques on these two data sets. He et al., 2023 suggest that an anomaly detection model should be used due to the shortage of labelled data for training[24].

For the prediction of multiple nodes' short-term energy consumption in manufacturing systems, Guo et al., 2022, proposed the Spatio-Temporal Deep Learning Network (STDLN) approach. The approach combines GCN and GRU to forecast the future energy consumption of six nodes. The topology modelling, spatial and temporal relationship learning networks, and modelling of topology are used to create a prediction algorithm. STDLN's RMSEs decreased by approximately 48, 56, & 19 (%) respectively. Mean Absolute Errors decreased by approximately 66, 71, & 21 (%) respectively, when compared with the Auto-Regressive Integrated Moving Average, XGT, & Support Vector Regression for prediction of the 5 min set. Higher accuracy values (76.70% at 76.90% and 32.70%) and higher R2 values (82.60%, 57.70% and 35.60%s) were observed[25].

Muñoz-Organero & Queipo-Álvarez, 2022 proposed a novel deep learning model for forecasting the spread of the COVID-19 virus inside a region over time. The model combines a time pattern extraction method using LSTM, RNN and a CNN with a prior spatial analysis method. Results showed better scores in terms of both RMSE and Explained Variance. The results of using the model to forecast a new wave revealed an appropriate approximation to the actual data for the whole wave, with the exception of the wave's beginning[26]. Incremental Spatio-Temporal Learner is a solution proposed by Nawaratne et al., 2020 to identify difficulties in anomaly localization and detection for real-time video surveillance. It uses active learning combined with fuzzy aggregation to collect the CUHK Avenue dataset and a focus on two pedestrian walkways to record the UCSD pedestrian Dataset. Incremental Spatio-Temporal Learner is based on a spatiotemporal Auto Encoder model made up of ConvLSTM layers that preserve the spatial structure of the video stream while learning temporal regularities [27].

Table-6: REVIEW OF SPATIO-TEMPORAL DATA ANALYSIS IN HEALTHCARE AND ENERGY

Reference	DL Model	Result
Guo et al.,2022	GCN & GRU	Compared with the XGT,RMSE decreased by 48.69% whilethe MAE decreased by 66.15%
Nawaratne etal., 2020	ISTL	Improvement in accuracy, robustness, low computational overhead

3. CONCLUSIONS

Spatio-temporal analytics using deep learning has emerged as a promising approach to tackle a broad range of problems in different domains such as agriculture, transportation, manufacturing, and environmental science. The reviewed studies highlights the importance of incorporating various data sources to enhance the accuracy and robustness of the models. The application of deep learning techniques in spatio- temporal analytics has opened up new avenues for solving complex problems that were previously deemed challenging or impossible. Despite the promising results there is still much to be explored in terms of model architecture, data fusion techniques, and interpretability of the models. Therefore, future research in this field should focus on developing more robust and interpretable models that can leverage the spatio-temporal data to its fullest potential. The interpretability of models is critical in many domains, such as environmental science, where the stakeholders need to understand the decision-making process behind the models to make informed decisions. Moreover, researchers should explore novel architectures, such as graph neural networks, attention mechanisms, and hybrid models, to better handle spatio-temporal data's complexities. Additionally, developing efficient data fusion techniques to combine diverse data sources can improve the robustness and generalizability of the models.

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