A Systematic Review of Deep Learning Applications in Interpolation and Extrapolation of Precipitation Data

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Abstract
With technological enhancements, the volume, velocity, and variety (3Vs) of the raw digital Earth data have increased in recent years. Due to the increased availability of computer resources and the growing popularity of deep learning applications, this data has been a crucial source for data-driven studies that have transformed the fields of climate and earth science. One of the critical data sources is precipitation supporting climate and earth science studies on modeling, forecasting, and preparedness for extreme events (i.e., floods, droughts, pollution transport). In this study, we worked on an extensive review of manuscripts focusing on use of deep learning methods to tackle challenges either to improve the quality or extrapolate (forecast) rainfall datasets. The purpose of this study is to summarize the most recent developments in deep learning approaches for forecasting rainfall or improving rainfall datasets, as well as highlighting issues, shortcomings, and open questions with insightful recommendations for future directions.

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1. Introduction

Raw digital Earth data is constantly produced by large-scale sensor, radar, and satellite networks. Many engineering tasks and activities such as environmental modeling (Ewing et al., 2022), decision making (Teague et al., 2021), and disaster preparedness (Alabbad et al., 2021), monitoring, and response rely on the transformation of these dataset into more comprehensible formats. Long-term sustainability and resilience studies (Alabbad et al., 2022) depend on how well these extensive amounts of data about earth is managed, which could significantly affect the research, practice, and policies on climate change in the next few decades (Grossman et al., 2015).

Computer-based solutions and systems have actively been used for environmental modeling for decades (Ramirez et al., 2022). Physical models run on computers to simulate hydrological and atmospheric events and changes in natural systems, allowing people to comprehend natural processes (Krajewski et al., 2021). Yet, natural systems are complicated and non-linear, making them difficult to completely comprehend before being conceptualized using mathematical and numerical representations (Demir and Szczepanek, 2017). Advanced data-driven techniques are widely applied in the field (Hu and Demir, 2021; Li et al., 2022) due to aforementioned reasons. Statistical models have been the go-to approach for modeling both linear and nonlinear systems, starting with conventional machine learning models and progressing to increasingly complicated deep learning approaches. Black box systems works for many tasks that were difficult to tackle in many areas, such as image recognition, speech to text systems, and translation. Earth and climate scientists have been using deep learning algorithms to simulate earth events, augment environmental data (Demiray et al., 2021a), and generate synthetic datasets (Gautam et al., 2020), using methodology from other domains of application research (Sit et al., 2022).

Significant number of studies have been published in recent years to take advantage of the opportunities created by the enormous Earth data, and some of these articles have directly focused on improving data quality and quantity. In the deep learning field, data augmentation and syntheses, such as super-resolution (Dong et al., 2015, Demiray et al., 2021b) or synthetic data generation (Han et al., 2018, Gregor et al., 2015) raise crucial opportunities and are widely investigated to improve overall efficiency and performance of methods where the data quality is important (Shorten and Khoshgoftaar, 2019). A similar case exists in hydrology and water management as well, especially for rainfall. As will be mentioned in this manuscript, many articles work on rainfall datasets in various aspects, such as downscaling of precipitation time series (Misra et al., 2018; Wang et al., 2020), increasing the spatial resolution of weather data (Rodrigues et al., 2018; Chen et al., 2019), bias correction over satellite precipitation products (Tao et al., 2016; Hu et al., 2021b), or synthetic weather data generation (Wang et al., 2019a; Guevara et al., 2021).

Rainfall forecasting is an important component of many studies in hydrology and water management (Darji et al., 2015; Kannan et al., 2010) such as flood prediction (Reynolds et al., 2020; Xiang et al., 2021), agricultural planning (Guido et al., 2020), watershed management (Sit et al., 2019). Many physical and data-driven approaches with varying characteristics, such as utilizing multiple data types, focusing on certain regions, or different generalization levels, have been presented throughout the years (Hussain and Zoremsanga, 2021; Haupt et al., 2021). With the recent progress in deep learning and the increased availability of different data sources, the number of approaches based on data-driven methods has skyrocketed, and many of the proposed methods leverage deep artificial neural networks (Sit et al., 2020).

This study reviews manuscripts that use deep learning to tackle challenges that either improve the quality of the rainfall data or forecast rainfall. Despite the interest, there are few studies that focus on the state of the literature in rainfall forecasting in terms of deep learning usage while describing challenges or limitations as well as possible ways to overcome shortcomings, and each of them has some limitations in terms of scope, cardinality, or emphasis. Also, to the best of our knowledge, there are no reviews in the field that cover the augmentation and extrapolation of precipitation datasets by utilizing deep learning. While some reviews and surveys provide an overview of primarily forecasting research, they do not address interpolation of rainfall in temporal and spatial domain.

As a result, the purpose of this study is to summarize the most recent developments in deep learning approaches for forecasting rainfall or improving rainfall datasets, as well as highlighting issues, shortcomings, and open questions with insightful recommendations for future directions. The rest of this study is organized as follows: The methodology for this review's literature survey will be discussed in section 2. The publications that were identified as belonging to the aforementioned scope will then all be briefly presented in section 3. Summary data, comprehensive results, and some open research problems will all be presented in section 4.

2. Methodology

In this review, Google Scholar was utilized as the main source for the scholarly work because it indexes all peer-reviewed and pre-print publications from a variety of sources. On Google Scholar, it is possible to find listings for manuscripts published by major publishers such as Elsevier, Springer, and Wiley, in addition to listings from pre-print services such as arXiv and EarthArXiv. Furthermore, Google Scholar includes an advanced search tool that allows users to define keywords and where those terms occur, in addition to the year the document was written. As a result, in this review, Google Scholar was used with various word combinations to find related articles. For the purpose of conducting search of manuscripts, two different lists of keywords were used; one list contains terms related to deep learning, and the other list contains terms linked to earth science. The complete list of keywords can be seen in Tables 1 and 2. In each of the searches, a keyword from each of the lists was combined, and the results were narrowed down to manuscripts published between the years 2014 and 2021 that contained both of the combined keywords in their titles. This historical period was selected for use for the following three reasons: (1) previous machine learning reviews and surveys for rainfall could not find much deep learning research prior to 2014; (2) beginning in 2014, a significant number of fundamental deep learning architectures were presented; and (3) deep learning works for rainfall that has received the most citations were released after 2014.

Table 1. Rainfall related keywords that were used in combination with deep learning keywords

Keywords				
hail	hailstorm	hurricane	hurricanes	meteorologic
meteorological	meteorology	nowcast	nowcasting	precipitation
radar echo	radar echoes	radar reflectivity	rain	rainfall
rainstorm	snow	weather		

A Python package, scholarly, was used to collect the information from Google Scholar. When a search is performed in scholarly, the package provides an iterator containing all the publicly accessible information for each matching manuscript on Google Scholar. The following fields were saved for each manuscript: title, authors, year, venue, URL, and abstract. After removing duplicates by title and URL, a total of 4,876 unique manuscripts remained among the obtained documents.

Prior to reviewing articles, an elimination process with two steps was followed. In the first step, by their titles alone, 4,876 manuscripts were categorized as relevant or irrelevant; articles with confusing names that lacked a clear focus were included in the relevant manuscripts list. At the second stage of the elimination process, each article was quickly scanned in order to figure out the architecture that was utilized as well as the purpose of the study. It was important to take this step in order to get rid of the articles that utilized artificial neural networks (ANNs), but not in the "deep learning" sense.

For the purposes of this article, we defined "deep learning" as the application of particular mainstream ANN architectures. These include Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) Networks (Hochreiter and Schmidhuber, 1997), Recurrent Neural Networks (RNNs), Gated Recurrent Unit (GRU) Networks (Cho et al., 2014), Autoencoders (AE), Deep Belief Networks (DBNs) (Hinton, 2009), Elman Neural Networks (ENNs) (Elman, 1993), Echo State Networks (ESNs) (Jaeger, 2007), and Generative Adversarial Networks (GANs) (Goodfellow et al., 2014). Even though the use of a fully connected ANN could satisfy the deep learning criteria, we decided to only include manuscripts that defined their methodology as deep learning and used more than one hidden layer in their architecture. With the use of this strategy, we were able to bring the total number of papers down to 196, which was a significant reduction.

Another point of this step was to eliminate studies that have equivocal keywords in their titles while the full text makes it obvious that they don’t fit within the scope of this review. For instance, the weather prediction field covers the prediction of many weather parameters; while rainfall is desired for this study, wind speed is not. Table A1 contains a list of the manuscripts reviewed in this study, as well as their classification and the deep neural network architectures utilized in them.

Table 2. Deep learning keywords that were used in combination with rainfall keywords

Keywords				
adversarial	ae	ai	albert	alexnet
ann	anns	antnet	attention	autoencoder
autoencoders	backprop	backpropagation	bart	bert
bigru	bigrus	bilstm	bilstms	birnn
birnns	camembert	cbam	cnn	cnns
convgru	convgrus	convlstm	convlstms	convnet
convnets	convolution	convolutional	convrnn	convrnns
cyclegan	dbn	dcgan	deep	delugenet
densenet	distilbert	distilgpt2	distilroberta	dqn
echo state	efficientnet	effnet	electra	elman
fcn	fractalnet	gan	gans	gated
generative	googlenet	gpt	gpt2	gpt3
gru	grus	inception	intelligence	lenet
long short term	long short time	lstm	lstms	machine
megatron	mobilenet	multi layer	neural	pggan
polynet	progan	pyramidalnet	recurrent	residual network
residual networks	resnet	resnext	resunet	rnn
rnns	roberta	rubert	sae	segnet
seq2seq	sequence to	spatial network	spatial networks	spatiotemporal network
spatiotemporal networks	stylegan	stylegan2	temporal network	temporal networks
transformer	transformers	unet	vae	vec2vec
vgg	vggnet	wav2vec2	xception	xlnet

3. Literature

In this section, we will summarize individual manuscripts, beginning with past deep learning review studies that at least partially cover the range of our work.

3.1. Review Papers

As it's expected for any topic that receives a significant amount of attention from academics, various comprehensive review studies covered deep learning application studies for precipitation augmentation and extrapolation. Despite covering fewer manuscripts than this study, they accomplished abstracting the idea of deep learning in the earth sciences as well as summarizing the relevant literature.

Sit et al. (2020) began by providing a summary of the state-of-the-art deep learning architectures as well as example deep learning tasks in order to provide the reader a foundation. Next, they provided an overview of each publication that fulfilled the requirements for their systematic review, which were deep learning studies in the fields of hydrology and water resources. Hussain and Zoremsanga (2021) presented a comprehensive survey of rainfall forecasting using deep learning where they analyzed the deep learning methods employed, the study area's location, the sorts of metrics and software used to create the model, and the publishing year of the articles. In a cardinality-wise more comprehensive study, Ren et al. (2021) presented a similar set of articles while including prediction tasks that involve any of many weather parameters. With a similar focus, Haupt et al. (2021) presented their inferences from the 2019 Oxford workshop on Machine Learning for Weather and Climate discussion. While they presented the challenges regarding available data, they also reviewed papers that forecast weather parameters. Fang et al. (2021a) narrowed down the focus to only cover studies that tackled the prediction of extreme weather events, meaning the prediction of rare climate occurrences.

To the best of our knowledge, there are no reviews in the field that cover the augmentation and extrapolation of precipitation datasets by utilizing deep learning. While the aforementioned reviews and surveys provide an overview of primarily forecasting research, they do not address interpolation of rainfall in time and space.

Precipitation forecasting is the primary category that the precipitation-related studies we review here fall into. In order to ensure a clear and understandable structure for the review, we decided to separate forecasting studies by the output structure of the model they proposed, excluding the temporal dimension. For instance, if a model proposed in a study forecasts a value or a sequence of values, then that study belongs to the 1D category. Conversely, if a model outputs a matrix of values or a sequence of matrices, then we review them in the 2D category, such as radar echo extrapolation. The following sections have organized the review in 1D and 2D rainfall forecasting, forecast improvement, and data augmentation and synthesis categories.

3.1.1. 1D Rainfall Forecasting

Rainfall forecasts for a single location could be categorized by their temporal resolution. However, there are some individual studies with temporal resolutions that would not form a set. For instance, in a study for 1-minute resolution, Wang et al. (2019b) utilized attention-BiLSTMs for Qinghai Lake, China. The model they proposed was trained over data with 1-minute resolution to forecast 48 hours of precipitation. For Jingdezhen, China, Kang et al. (2020) forecasted meteorological variables with 3 hours of temporal resolution using LSTMs. Conversely, for annual precipitation forecasts in East Kalimantan, Indonesia, Putra et al. (2020) trained CNNs and compared them to ANNs. The rest of the studies that forecast 1D rainfall instead of matrices were split into hourly, daily, and monthly.

Hourly – In early hourly precipitation forecast studies that employed deep learning, LSTMs were frequently used. Kim and Bae (2017) calculated the Precipitable Water Vapor (PWV) based on the tropospheric delay of the Global Navigation Satellite System signals. Their experiments showed that LSTMs perform better than ANNs. With a different architectural choice, Zhang et al. (2018) employed DBNs powered by environmental factors to output 24 hours of forecasts for 4 locations in China. Similarly, for Nanjing Station, China, Du et al. (2018) forecasted hourly precipitation as a function of various weather parameters such as atmospheric pressure and relative humidity. In an ESN study, Yen et al. (2019) forecasted precipitation for Tainan Observatory in southern Taiwan and compared the ESNs to SVMs. Manokij et al. (2019), trained a ConvGRU for Taiwan. Similarly, Hewage et al. (2020) trained a TCN and an LSTM for 10 weather parameters, including precipitation, with data from a Raspberry Pi-based sensor. They showed that TCNs performed slightly better. In another study focusing on convolutions, Wei (2020) forecasted hourly and daily precipitation for construction sites and their management. For greenhouse environmental control, Hsieh et al. (2020) utilized LSTMs.

Senekane et al. (2021) explored RNNs and ENNs for sunshine and precipitation forecasting. In a recurrent network study, Chen et al. (2021b) employed LSTMs for Axim, Ghana. Using seven weather parameters, they forecasted precipitation and compared their LSTM to ANNs. For forecasting rainfall up to 12 hours using surface weather parameters, Hewage et al. (2021) trained LSTMs and TCNs over global weather data and compared them to various classical machine learning approaches. Manokij et al. (2021) utilized GRUs and CNNs. CNNs were used first to classify if there was rain, then GRUs forecasted rain for Taiwan. Lastly, Narejo et al. (2021) trained DBNs and CNNs for forecasts up to 8 hours for the Neuronica Laboratory, Italy.

Daily – For accumulated precipitation of the next day, Hernández et al. (2016) trained a neural network comprising an autoencoder followed by dense layers for Manizales, Colombia. Without the autoencoders abstracting the data beforehand, Gorshenin and Kuzmin (2018) explored ANNs for two-step daily forecasts for two cities in Europe, Potsdam and Elista. In a study with a more complex network, Lohani (2019) forecasted daily precipitation for Punjab, India with LSTMs. Coupling the moving average approach with LSTMs, Caraka et al. (2019) presented a model for Winangun, North Sulawesi, Indonesia. Similarly, Atika et al. (2019) for 3 gauges in Surabaya, Indonesia and Miao et al. (2019) for the Xiangjiang River Basin in South China utilized LSTMs. For a global weather dataset by the National Oceanic and Atmospheric Administration (NOAA), Wu et al. (2019) trained various networks, namely, ANNs, LSTMs, and CNNs. Poornima and Pushpalatha (2019) presented Intensified LSTMs that were trained with the China Meteorological Administration (CMA) open dataset. They compared LSTMs to RNNs and ELMs. In another LSTM study, Chaurasia et al. (2020) forecasted daily precipitation for Yamuna Nagar district in Haryana, India using NASA datasets. Conversely, Khan and Maity (2020) for Maharashtra, India; Chong et al. (2020) for Langat River Basin, Malaysia; Bajpai et al. (2020) for Rajasthan, India trained CNN models using weather parameters.

In 2021, LSTM-based studies gained traction. Ponnoprat (2021) proposed an autoencoder consisting of two LSTMs. They forecasted precipitation for two locations with different climates: Chiang Mai International Airport, Chiang Mai, Thailand; and Theodore Francis Green State Airport, Providence, Rhode Island, United States. In a comparative study of LSTMs with SVMs and Random Forests, Hou et al. (2021) explored data-driven precipitation forecasts for Yibin City, Sichuan, China. Similarly, for Jimma, Ethiopia, Endalie et al. (2021) compared ANNs, k-Nearest Neighbors (KNN), SVMs, and Decision Trees. In both studies, they showed LSTMs performed better. In order to compare various deep learning models for various locations in Malaysia, Ramlan and Mohd Deni (2021) trained ANNs, LSTMs, and ConvLSTMs.

Likewise, Latifoğlu (2022) utilized bidirectional LSTMs for the Churchill River in Canada. In other studies that employed LSTMs, Haq et al. (2021) for East Java, Indonesia and Chai and Goh (2021) for Sarawak, Malaysia forecasted precipitation using various weather parameters. Hammad et al. (2021) explored LSTMs and various combinations of wavelet transform powered ANNs as well as time-lagged ANNs for three meteorological stations in Pakistan. They showed that all models performed similarly, except for straightforward time-lagged ANNs, which were slightly worse. Combining Chebyshev polynomials (CP) with ANNs, Guo et al. (2021) used weather data to train LSTMs followed by ANNs with CP as the activation function. Soundararajan (2021) forecasted rainfall for the next day using weather parameters employing a CNN for Australia. Finally, in a GAN study, Venkatesh et al. (2021) employed LSTMs as the generator in the GAN to take advantage of their performance over sequential data for India.

Monthly – Ouyang and Lu (2018) utilized ESNs and compared them to SVMs for Jilin Province, China. In another ESN study, Xu et al. (2018) forecasted rainfall for 12 cities in China by building a spatio-temporal structure among them. Using atmospheric parameters on ANNs, Weesakul et al. (2018) and Mahat et al. (2020) forecasted monthly rainfall for Pluak Deang, Thailand. Utilizing RNNs, Saikhu et al. (2018) presented an approach for spatio-temporal forecasts in three stations in East Java, Indonesia. In another study that employed recurrency in their network, Aswin et al. (2018) compared LSTMs to CNNs for global monthly rainfall forecasts. Similarly, Haidar and Verma (2018) employed CNNs for monthly forecasts in eastern Australia. Lee et al. (2020) forecasted monthly precipitation for the Han River Basin, South Korea using lagged climate indices.

In other LSTM studies, while Samad et al. (2020) and Khan et al. (2020) forecasted precipitation using LSTMs for Australia and Bangladesh, respectively, Oswalt Manoj and Ananth (2020) utilized convolutional LSTMs for India. In a comparative study for Thimphu, Bhutan, Chhetri et al. (2020) trained ANNs, LSTMs, BiLSTMs, and GRUs, as well as a BiLSTM-GRU combination. They showed that LSTMs performed best among vanilla architectures, while BiLSTM-GRU performed best overall. In a similar sense, da Cunha Mariano (2020) compared CNNs, LSTMs, Encoder-Decoder LSTMs, Encoder-Decoder ConvLSTMs and a CNN-Encoder-Decoder-LSTM combination using climate indices for global data. They showed the CNN-Encoder-Decoder-LSTM combination performed best among their candidates.

In 2021, Weesakul and Chaiyasarn (2021) explored ANNs for the Ping River Basin, Thailand. Similarly, Harsa et al. (2021) used climate data for Japan to train an ANN and compared it to XGBoost, showing they perform comparably. For monsoon rain in India, Bajpai and Bansal (2021) compared ANNs and 1D CNNs. Their proposed deep and wide ANN outperforms the CNN. In another comparison of ANNs, Kanchan and Shardoor (2021) trained ANNs, RNNs, and LSTMs for Karnataka, India. They showed that LSTMs performed the best. Likewise, Duong et al. (2021) compared ANNs to LSTMs for Ca Mau, Vietnam and showed that LSTMs performed best. Tao et al. (2021) combined wavelet transforms and attention LSTMs for 129 stations in the Yangtze River basin. Similarly, Wu et al. (2021) combined wavelet transform, ARIMA, and LSTMs for northeast China. Zhang et al. (2021c) compared CEEMD-LSTMs and CEEMD-ANNs for Zhengzhou, China and showed that they performed comparably. Finally, Sugiyarto and Rasjava (2021) for Yogyakarta, Indonesia, and Kala et al. (2021) for the Indian Monsoon rain, trained LSTMs.

3.1.2. 2D Rainfall Forecasting

Beyond rainfall forecasting, prediction of 2D tensors has been an attractive problem to tackle among computer vision researchers for video frame prediction. Consequently, the attention of the scientific community to this problem is quite different from the attention that 1D rainfall forecasting and streamflow forecasting get. Unlike the studies we have reviewed so far, some 2D rainfall forecasting studies built solutions that were compared with their antecedents. The use of the same datasets to show how new approaches perform compared to previous ones has been done in some of the 2D rainfall prediction studies we will review in this subsection. Although these studies utilized 2D sequences of, mostly, radar echoes to build models, they often used datasets of a similar nature, such as Moving MNIST (Srivastava et al., 2015). Because of the cumulative nature of some studies within this category with the intention of producing better networks rather than creating another application, we chose to review them separately. Thus, we will review them in the state-of-the-art subsection. After these well-known architectures, we will review the remainder of the 2D precipitation forecast studies, categorizing them, again, depending on their temporal resolution.

State-of-the-art - 2D forecasting of rainfall starts with ConvLSTMs and ConvGRUs thanks to research on video frame forecasts (Mathieu et al., 2015). Shi et al. (2015) proposed the use of ConvLSTMs for radar echo forecasts, feeding the network with 5 frames totaling 30 minutes of data and training it to forecast 15 frames for 1.5 hours in total. They compared their results to an extrapolation method, ROVER. Improving what convolutional recurrent architectures achieve, Shi et al. (2017) proposed Trajectory GRU (TrajGRU), which is an encoder-decoder architecture where the input frames go through a series of downsampling and RNN layers in the encoder part, then go through a series of RNN and upsampling layers in the decoder (namely the forecaster) part to finally output the forecasts. With the idea of providing an option that is location-variant as opposed to location-invariant ConvRNNs, TrajGRU was tested on the HKO-7 radar echo dataset for Hong Kong as well as Moving MNIST and was shown to be better than ConvLSTM, ConvGRU, 2D CNNs, and 3D CNNs. In another attempt, Recurrent Dynamic CNNs (RDCNN) were proposed by Shi et al. (2018). RDCNN is made up of a recurrent dynamic sub-network and a probability prediction layer that builds a cyclic structure in the convolution layer, allowing it to process time-related frames better. Radar data from Nanjing, Hangzhuo, and Xiamen in China were used for case studies, and the performance of RDCNN over them was compared to older approaches, such as the strong COTREC method.

Jing et al. (2019a) presented Multi-Level Correlation Long Short-Term Memory (MLC-LSTM) and how to incorporate adversarial training into their method. As the generator, they constructed an encoder–predictor architecture based on the MLC-LSTM for end-to-end radar echo extrapolation, followed by a CNN structure as the discriminator. Networks were trained with both image loss and adversarial loss, resulting in a more fine-grained and realistic extrapolation of echoes. In Luo et al. (2020), the authors proposed a new pseudo flow spatiotemporal LSTM unit (PFST-LSTM), which incorporates a spatial memory cell and a position alignment module into the LSTM. They tested PFST-LSTM units for 2D forecasting over the Moving MNIST dataset, which showed the architecture can efficiently combine spatial appearances and velocity information. They also showed PFST-LSTM beats TrajGRU as well as 2D forecasting architectures from non-radar-echo-forecasting literature such as PredRNN (Wang et al., 2017) and ST-LSTM (Tang et al., 2019). Cao et al. (2019) suggested an RNN-based star-bridge network (StarBriNet). The suggested network has many sub-networks to deal with varied rainfall intensities and durations separately, which can increase the model performance. They also designed a star-shaped information bridge to improve data flow between the RNN layers. To account for the precipitation nowcasting, the networks were trained with a multi-sigmoid loss function. They compared their approach to ConvLSTM and Conv3D for 6 minutes of resolution.

Xie et al. (2020) proposed an energy-based GAN, EBAD, where the generator is ST-LSTM based and the discriminator yields low energy for real data and high energy for generated data. The authors compared EBAD to ConvGRUs, generative adversarial ConvGRUs, and optical flow over Guangdong, China. Zhong et al. (2020) proposed spatiotemporal convolutional long short-term memory (ST-ConvLSTM), which uses the attention mechanism to simulate long-range and long-term spatiotemporal dependence and uses ConvLSTM to collect coarse spatiotemporal information. The authors compared their technique to ConvLSTM, ConvRNN, PredRNN, and the ConvGRU version of the suggested architecture: ST-ConvGRU over Moving MNIST and radar echoes for Guangzhou, China. For radar-based precipitation nowcasting, Ayzel et al. (2020) proposed a CNN, RainNet. The U-Net and SegNet models, which were originally created for binary segmentation problems, were the inspiration for the RainNet. Using several years of quality-controlled weather radar data for Germany, RainNet was trained to estimate continuous precipitation intensities with a 5-minute lead time. A recursive technique was employed to attain a 1-hour lead time by employing RainNet predictions at 5 minute lead times as model inputs for longer lead times. The approach was compared to persistence, which assumes the prediction is the same as the last known frame, as well as Rainymotion, which is an optical flow based 2D forecast library. Borrowing the ideas from RainNet, Zhang et al. (2020a) presented Tiny-RainNet, combining CNNs and BiLSTMs.

Sønderby et al. (2020) presented a ConvLSTM-powered architecture, MetNet, which provided a solution to the problem of precipitation forecasting with accurate forecasts for up to eight hours over a 1 km x 1 km area. For the continental United States, 2-minute resolution data was used. MetNet is capable of outperforming the HRRR (High Resolution Rapid Refresh) (NOAA, 2014) system while creating probabilistic precipitation maps using radar data, satellite data, and forecast lead time as inputs. Incorporating cumulative rainfall data from rain gauges, Espeholt et al. (2021) improved MetNet and presented MetNet-2. Shen et al. (2021) proposed an encoder-decoder ConvRNN, namely EDD, over SRAD2018 data (Aliyun, 2018) and compared it to RainNet and ConvLSTMs.

Similar to MetNet and MetNet-2, RainfallNet (Huang et al., 2021) proposed a fusion module where radar echo observations and numerical weather prediction (NWP) data are integrated. The architecture consists of three components: (1) dual encoders for extracting spatio-temporal features from radar echo images and NWP data; (2) combining channel and spatial attention; and (3) a loss function combining structural similarity loss, mean square error, and mean absolute error with different weights for each rainfall level to further increase the sensitivity. They compared RainfallNet to TrajGRU, ConvLSTM, PredRNN++ (Wang et al., 2018) which is an improved version of PredRNN, and RainfallNet without fusion.

Yan et al. (2021) introduced the Flow-Deformation Network (FDNet), a neural network that predicts flow and deformation in two parallel cross paths. FDNet proposed decomposing the movement into optical flow field motion and morphologic deformation to effectively manage the complex and high non-stationary evolution of radar echoes. The deformation encoder detects the change of shape from the translational motion of radar echoes, whereas the flow encoder catches the optical flow field motion between consecutive frames. The authors compared the FDNet to ConvLSTM as well as state-of-the-art methods such as TrajGRU. Klocek et al. (2021) presented MS-nowcasting, which is an encoder-decoder ConvLSTM architecture where atmospheric models such as HRRR could be incorporated into the process. The authors showed versions of the proposed model that were fused with atmospheric models performed better than the vanilla version for the US and Europe.

Luo et al. (2021a) proposed Interactional Dual Attention Long Short-term Memory (IDA-LSTM), which incorporated (1) an interaction scheme between the hidden state and the input of LSTMs, and (2) a dual attention module for both channel and temporal information to improve long-term spatiotemporal recognition. Over the CIKM AnalytiCup 2017 data (CIKM Conference, 2017), they compared IDA-LSTM against ConvLSTM, ConvGRU, TrajGRU, PredRNN, PredRNN+, E3D-LSTM, and MIM. In another approach, Luo et al. (2021b) proposed incorporating Region Attention Block (RAB) into ConvRNNs to improve forecasting in areas with heavy rainfall, namely RAP-Net. To improve the prediction, they also presented the Recall Attention Mechanism (RAM). RAM improves forecasting by maintaining longer temporal information. Their experiments showed that RAP-Net performed better than many state-of-the-art architectures, among them being TrajGRU and PFST-LSTM. Again, Luo et al. (2022) proposed the PredRANN (ConvRNN) model in which the Temporal Attention Module (TAM) and Layer Attention Module (LAM) are embedded in the prediction unit to maintain more temporal and spatial representation, respectively. Similarly, Nie et al. (2021) compared Optical Flow Attention Fusion ConvLSTM (OFAF-ConvLSTM) to TrajGRU and PFST-LSTM. OFAF-ConvLSTM embedded an attention mechanism and optical flow methodology into ConvLSTMs and built an encoder-decoder architecture. Zhang et al. (2021d) proposed a convolutional AE-LSTM fusion and compared it to TrajGRU and ConvLSTM. Likewise, compared to TrajGRU, Xiong et al. (2021) proposed Contextual Spatial Attention Convolutional LSTM.

To provide a fast-working architecture, Castro et al. (2021) proposed STConvS2S (Spatiotemporal Convolutional Sequence to Sequence Network). The STConvS2S consists of only convolutional layers, and the authors showed that STConvS2S worked faster than PredRNN for the radar echo forecasting task. Niu et al. (2021) proposed a two-stage spatiotemporal context refinement network (2S-STRef), which is two-fold as the name suggests. The first stage is a spatiotemporal prediction network that gives a first-stage prediction using a spatiotemporal RNN module incorporated into an encoder-decoder framework. The suggested detail refinement network is the second stage. Fang et al. (2021b) proposed the AttEF (Attention ConvLSTM Encoder-Forecaster). In AttEF, the encoder can encode all spatiotemporal information into a sequence of vectors. The Moving MNIST and a radar echo dataset from the Shaanxi Province were used to test the system with ten input and ten output frames. They compared the performance of their approach to that of ConvLSTM, TrajGRU, and PredRNN.

5-Minutes – Using a radar echo dataset for Germany, Ayzel et al. (2019) employed a CNN. They evaluated various data preprocessing routines to find the best combination. This study was, in a way, a premise for RainNet. In a similar fashion, Teo (2019) explored LSTMs, GRUs, and ConvLSTMs for radar echo in Singapore, where they also utilized the Moving MNIST in training. French et al. (2020) employed TrajGRU for a model to forecast rainfall in Italy. Their dataset, namely, TAASRAD19, had a 500 m spatial resolution and they forecasted 20 frames (100 minutes) from 5 frames (25 minutes) of input. In an attempt to forecast radar reflectivity data for up to an hour for Brazil, Bonnet et al. (2020) trained a PredRNN++. Marrocu and Massidda (2020) explored GANs in radar echo forecasts for up to an hour (12 frames) for Japan. They compared their approach to various OpticalFlow algorithms. Similarly, Schreurs et al. (2021) utilized GANs for the Netherlands. They compared their approach to an extrapolation model, S-PROG. Utilizing Unet, Trebing et al. (2021) employed attention and depth wise-separable convolutions to forecast precipitation maps for Netherlands. Again, for the

Netherlands, van der Kooij (2021) utilized TrajGRU. In another Unet study, utilizing weight superposition, Khorrami et al. (2021) forecasted weather for the contiguous US by taking advantage of transfer learning. They compared their approach to different variations of Unet and persistence. In a Unet-based study, Fernández and Mehrkanoon (2021) proposed Broad-Unet where the pooling is only performed in the spatial dimensions. The authors compared their approach to Unet, CNNs, LSTMs, and RNNs for cloud cover datasets and precipitation maps. On the SEVIR dataset (Massachusetts Institute of Technology, 2020) for the US, Hu et al. (2021a) presented a GAN with two discriminators; one spatial and the other spectral. Finally, Xu (2021) utilized LSTMs for radar extrapolation in China and compared the model to optical flow.

6-Minutes – Nguyen et al. (2017) used Residual Convolutional LSTMs for radar data with multiple channels for multiple heights. Similarly, Kim et al. (2017) employed ConvLSTMs for China. Wu (2019) employed an encoder-decoder structure based on ConvLSTMs and trained it on CIKM AnalytiCup 2017 data by the Shenzhen Meteorological Bureau and Alibaba. Tran and Song (2019a) compared TrajGRU, ConvLSTM, and ConvGRU over the CIKM AnalytiCup 2017 data to predict 10 future steps. Again, Tran and Song (2019b) applied ConvLSTMs, ConvGRUs, TrajGRU, PredRNN, and PredRNN++ for 3D radar images with four different elevation angles. In a star bridge network study, Chen et al. (2020a) trained Shanghai data and compared it to the TREC (tracking radar echo by correlation) method. In another attempt, Yao et al. (2020) incorporated a new loss function that focuses on changes in the sequence in an adversarial sense. They compared their approach toTrajGRU. Extending Progressively Growing GANs (PG-GANs) for radar echo forecasts over Hong Kong, MPL-GAN with ConvLSTM in the generator was proposed by Liu and Lee (2020). Using the CIKM AnalytiCup 2017 data, Yan et al. (2020) proposed a residual CNN with multi-head attention. They compared their approach to traditional machine learning algorithms.

Utilizing SRAD2018 data, Chen et al. (2020b) utilized 3D CNNs and Bidirectional ConvLSTMs and compared them to ConvLSTMs and ROVER. Similarly, Sun et al. (2021) employed Conv3DGRUs to predict 2 hours of rainfall and compared the model to Conv2D and Conv2DGRUs. For Dallas Fort Worth, Cuomo and Chandrasekar (2021) presented a residual CNN and compared it to TrajGRU and RainNet for their dataset. Despite promising results, ConvGRUs tend to forecast blurry radar echoes and fail to depict skewed distributions of radar echo intensities. Yin et al. (2021a) used the structural similarity (SSIM) and multiscale structural similarity (MS-SSIM) indexes as loss functions to solve these drawbacks. Utilizing a Unet based CNN, FURENet, Pan et al. (2021) forecasted 1-hour of rainfall over a C-band dual polarization weather radar operated by Nanjing University and compared it to TrajGRU. Finally, Czibula et al. (2021) and Socaci et al. (2021) developed an ANN and a ConvLSTM, respectively, for Romania.

10-Minutes – Klein et al. (2015) employed dynamic CNNs for Davenport, Iowa, Kansas City, Missouri, and Tel Aviv, Israel with 10-minutes of temporal resolution. With a 3D sequence to sequence convLSTM model, Heye et al. (2017) proposed a model that works on NEXRAD level 2 radar data (NOAA, 1988). Similarly, for NEXRAD data, Samsi et al. (2019) explored parallelization options over GPUs for nowcasting CNNs. For Japan, Baron et al. (2021) trained a Conv3DGRU network and compared it to an operational advection correction method. Danpoonkij et al. (2021) utilized Unet with a warping scheme for Japan. They compared their approach to Unet without the warping scheme and Optical Flow from Rainymotion. Choi and Kim (2021) presented a conditional GAN architecture for the Soyang-gang Dam region in South Korea. They compared their approach to UNet, ConvLSTMs, and persistence. Similarly, using a conditional GAN, Kim and Hong (2021) predicted radar rainfall products for South Korea. Finally, for Japan, Tosiri et al. (2021) forecasted 30 minutes of rainfall utilizing UNet by inputting 30 minutes of data.

12-Minutes – Niu et al. (2020), integrated radar echoes and temperature maps into a 3D tensor. They trained them over a multi-channel ConvLSTM and compared the approach to traditional machine learning models.

15-Minutes – For Weather4cast 2021 challenge (Institute of Advanced Research in Artificial Intelligence, 2021), in which the goal was to predict the next 32 frames from the last 4 frames, Leinonen (2021) presented a Unet-like encoder-decoder ConvGRU. While Choi et al. (2021) utilized Unet for the same challenge, Bojesomo et al. (2021) employed Video Swin Transformers. In order to forecast satellite weather data, Ionescu et al. (2020) proposed a CNN. They compared their approach to a vanilla CNN with satellite data that covers Europe and Africa.

20-Minutes – Using meteorological data, such as precipitation, along with non-meteorological but relevant data such as topography, Miao et al. (2020) proposed a multimodal semi-supervised deep graph network that is able to infer spatiotemporal correlations for China. For Next Generation Radar (NEXRAD) data in Denver and Dallas Fort Worth, Kim and Chandrasekar (2021) explored ConvGRUs, residual CNNs, and residual GRUs.

30-Minutes – Jing et al. (2019b) proposed a GAN consisting of one generator and two discriminators, one for individual frames, and another one for the sequence. The authors compared the proposed model to ConvLSTMs, TREC, and optical flow. Utilizing CNNs, Kumar et al. (2020) proposed Convcast that forecasts the next frame from 10 frames of input from NASA's IMERG dataset (NASA, 2014). Using the same dataset, Gamboa-Villafruela et al. (2021) proposed a ConvLSTM by comparing the model to multiple layers of the same architecture. Using the IMERG dataset again, Ehsani et al. (2021) presented a few Unet-like ConvLSTM structures and compared them to linear regression and random forest models. For the UK, Ravuri et al. (2021) proposed a GAN and compared the approach to Unet, the axial attention model, and the radar-only version of the MetNet. Finally, Zhang et al. (2021b) developed a dual-input dual-encoder recurrent neural network, RN-Net. RN-Net consists of multiple TrajGRU-based encoders that expect radar data as well as weather station data and outputs 2 hours of predictions for Southeastern China. The authors compared their approach to PredRNN, TrajGRU, and ConvLSTM. The Multi-Source Data Model (MSDM) was proposed by Li et al. (2020), which integrates optical flow, random forest, and CNNs. MSDM employed optical flow to forecast four frames of satellite data to decrease the smoothing generated by convolution. For the flood season in China, the authors compared MSDM against Unet, ConvLSTM, and optical flow alone.

1-2 Hour – Asanjan et al. (2018) presented an LSTM network combined with Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Hsu et al., 1997) for Oregon, Oklahoma, and Florida. They compared their approach to RNN, persistence, and optical flow. Agrawal et al. (2019) proposed an approach based on Unet for the NEXRAD dataset. They compared their results to optical flow, persistence, and NOAA's HRRR product. Combining rain gauge data, radar data, and satellite data for precipitation, Yadav and Ganguly (2020) built a CNN for up to 2 hours of rainfall forecasts for the US. The authors compared their model to optical flow and persistence. For Taiwan, Wei and Hsieh (2020) proposed a CNN and an ANN. Similarly, for Taiwan, Chen et al. (2021a) proposed an adversarial encoder-decoder approach and compared it to TrajGRU. For up to six hours of forecasts for Taiwan, Wei and Huang (2021) proposed a CNN as well as an ANN. Zhang et al. (2021a) proposed an LSTM architecture for Southeastern China and compared it to the Weather Research and Forecasting (WRF) Model for the same region. While Yasuno et al. (2021) presented a ConvLSTM for Japan, Yao and Chen (2021) designed an encoder-decoder ConvRNN to show how rain type affects 2D nowcasts.

3-Hours – To forecast 24 hours of precipitation, geopotential height and temperature for Europe Bihlo (2021) trained a conditional GAN over 4 years of ERA5 reanalysis data (European Centre for Medium-Range Weather Forecasts, 1979). They compared their approach to the European Centre for Medium Range Weather Forecasts (ECMWF) model.

6-Hours – Chen (2020) presented a ConvLSTM based on Unet using the Tropical Rainfall Measuring Mission (TRMM) (NASA, 1997) to predict 1 step into the future. To predict geopotential, temperature, and precipitation at 5.625° resolution up to 5 days ahead, Rasp and Thuerey (2021) utilized a deep residual convolutional neural network over WeatherBench data (Rasp et al., 2020).

Daily – Tian et al. (2019) employed adversarial training using ConvGRUs to overcome the blurry outputs a typical ConvGRU produces in radar echo forecasts. Authors show that their approach outperformed ConvGRUs and optical flow for Guangdong, China. In one of the rare studies that employed transformers, Civitarese et al. (2020) forecasted daily precipitation quantiles by training a temporal fusion transformer (TFT) model. The authors compared the TFT to the ECMWF model for Rio de Janeiro, Brazil and Florida, USA. Finally, for up to five days of daily forecasts, Chen and Wang (2021) presented a 3D CNN for the contiguous United States.

3.1.3. Forecast Improvement

Deep learning for rainfall forecast improvements appears somewhat later in the literature. Zhang et al. (2020b) employed LSTMs for postprocessing of 12 hours of forecasts. Using a correlation study of predicted meteorological parameters and real-time rainfall, eight significant meteorological elements were chosen. The K-means clustering approach was used to split the samples into four types. LSTMs were then used to simulate each kind in order to adjust rainfall estimates in eastern China. Similarly, using LSTMs, Llugsi et al. (2020) improved rainfall forecasts for Quito, Ecuador.

Forecasted 2D rainfall frames were aggregated by de Ruiter (2021) and turned into probabilistic output forecast frames using CNNs, rather than post-processing predictions on a per-pixel basis, as is typical when applying machine learning in meteorological post-processing. The authors showed that regularized logistic regression did not outperform CNNs. IC-MLNet, a multi-layer neural network for ensemble precipitation predictions postprocessing, was proposed by Xu et al. (2021), which reduces ensemble forecast bias while merging them into a deterministic forecast. A set of state-of-the-art statistical ensemble post-processing approaches were outperformed by IC-MLNet. Zhao et al. (2021) proposed a CNN approach. The approach first draws a flow field diagram using the ECMWF physical quantity field, then feeds it into the CNN for feature extraction.

Ghazvinian et al. (2021) used the Global Ensemble Forecast System (GEFS) to evaluate their proposed ANN-CSGD model for post-processing ensemble mean predictions of 24-hour precipitation totals over selected river basins in California, with one- to seven-day lead periods. The authors showed that their approach outperforms the EMOS (Ensemble Model Output Statistics) method. Using the data obtained from a radar forecasting system named McGill Algorithm for Precipitation nowcasting by Lagrangian Extrapolation (MAPLE) (Germann and Zawadzki, 2002) and ground rain gauges, Nguyen et al. (2021) employed LSTMs. They showed that LSTMs significantly improved MAPLE forecasts for South Korea. By utilizing a loss function that penalizes rare extremes in rainfall data, Hess and Boers (2021) presented an ANN approach and showed that their approach notably improved rainfall forecasts over the TRMM product of NASA. For the Huaihe River basin in China, Li et al. (2022) employed a CNN, as supplementary predictors to leverage geographical information and atmospheric circulation factors.

3.1.4. Data Augmentation and Synthesis

Bias Correction – In order to perform bias correction over satellite precipitation products, Tao et al. (2016) employed stacked AEs. They applied their method over Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks Cloud Classification System (PERSIANN-CCS) (Hong et al., 2004) to prove the concept over infrared imagery. Similarly, utilizing autoencoders along with CNNs in a Convolutional Autoencoders for pixel-by-pixel bias correction over satellite precipitation products, Le et al. (2020) employed Asian Precipitation-Highly Resolved Observational Data Integration towards Evaluation (APHRODITE) (Yatagai et al., 2012) for ground truth and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR) (Ashouri et al., 2015) as the input data. They evaluated their approach by comparing it to another bias correction method based on the standard deviation method they introduced. Hu et al. (2021b) proposed a CNN based on Unet to correct biases over Yin–He global spectral model (YHGSM) by inputting the geopotential, specific humidity, and vertical velocity on three pressure levels.

Clutter Removal & Error Detection – For weather radars in San Carlos de Bariloche, Argentina, Rosell et al. (2020) implemented an ANN to remove clutter from precipitation products. Lepetit et al. (2021), for France, devised a weakly supervised learning approach for clutter removal that enables them to avoid the problem of a lack of ground truth data. Their approach used Unet and required data from rain gauges. In an attempt to improve rainfall products, the fault diagnosis problem was defined by Li et al. (2019) as anomaly detection in time series. They used an LSTM model to simulate the status generated by the radars and forecast future status based on past data. Time periods with substantial forecast errors can be detected as faults based on the notion that anomaly deviates from normal data.

Synthetic Data Generation – In order for synthetic weather data generation, Wang et al. (2019a) utilized GANs for weather radar base data generation. Statistical analysis revealed that their synthetic data had the same properties as actual weather radar base data, with no non-meteorological noise. Similarly, Guevara et al. (2021) employed GANs and variational autoencoders. Mitra (2020) employed CNNs and autoencoders to simulate maps for rainfall as well as maximum and minimum temperatures. They showed this architecture could be used for the generation of new maps and downscaling of the weather maps depending on the training process.

Imputation – Chiu et al. (2021) proposed a spatial imputation method based on LSTMs optimized by a sine-cosine algorithm. In their approach, PCA was used to extract the most important features from the meteorological data prior to imputation. The PCA's final result is paired with rainfall data from nearby gauging stations and then utilized as the input to a neural network for missing data imputation. In order to impute arbitrary missing frames in a sequence of 2D rainfall maps, Gao et al. (2021) proposed using CNN-BiConvLSTMs and 3DCNNs. They demonstrated that the approaches they proposed outperformed optical flow and linear interpolation. In a structurally similar take, Sit et al. (2021a) proposed a CNN, namely TempNet, to increase radar rainfall resolution from 10 minutes to 5 minutes over the IowaRain (Sit et al., 2021b) dataset. In order to fill blocked areas in radar echoes, Yin et al. (2021b) proposed an ANN, namely an echo-filling network (EFnet). They used Nanjing S-band new-generation Doppler weather radar of China as a case study.

Super-resolution – In order to increase spatial resolution of weather data, Rodrigues et al. (2018) proposed a CNN. They compared their model to linear interpolation and showed that deep learning has great potential in super-resolution of weather maps. Using the S-band China New-Generation Weather Radar (CINRAD-SA) (China Meteorological Administration CINRAD Program, 2004), Chen et al. (2019) proposed utilizing GANs for high resolution radar echoes. Similarly, Yuan et al. (2021), using reflectivity data from CINRAD-SA, utilized CNNs for 2x and 4x super-resolution of weather radar echoes.

Downscaling – Misra et al. (2018) utilized LSTMs for downscaling of precipitation time-series for the Mahanadi River basin in India and the Campbell River basin in Canada. For downscaling of precipitation data in the Northeastern United States, Vandal et al. (2019) employed deep autoencoders along with several traditional machine learning models. Wang et al. (2020) utilized LSTMs and ANNs to downscale precipitation, maximum and minimum temperatures for various locations in China. They showed that LSTMs and ANNs performed differently in different regions, and there was no clear winner. Sha et al. (2020) downscaled 2D orographic convection maps employing CNNs. Similarly, for 2D downscaling of precipitation, Chaudhuri and Robertson (2020) employed GANs. They tested various loss functions for their generator and reported their performance over Great Bear Lake, Canada. For Indian summer monsoon rainfall, Kumar et al. (2021) employed three super-resolution methods: SRCNN (Dong et al., 2015), stacked SRCNN, and DeepSD (Vandal et al., 2017). They explored the models for up to 4x downscaling and showed the DeepSD model performed better than its competition. Tu et al. (2021) employed CNNs. They first utilized ERA-Interim datasets (European Centre for Medium-Range Weather Forecasts, 2006) for their approach, then applied it for super resolution of precipitation in the Kuma River Watershed in Japan. With the use of large-scale atmospheric variables from the ERA-Interim and high-resolution gridded data as predictors and predictands, Sun and Lan (2021) introduced CNNs to downscale daily temperature and precipitation across China. For North Africa, Babaousmail et al. (2021) employed convolutional autoencoders to emulate the downscaling of eight General Circulation Models (GCM) rainfall projections.

4. Results

In this section, we will provide a summary of findings from the review, and we will also present the conclusion that we derived from those findings. We will begin by looking at basic statistics that will help in the comprehension of deep learning applications in rainfall. In the Findings section, we will discuss our observations of the current state of the literature, including how it has evolved beyond the statistics and how it might change in the future. Then, we'll list some open questions.

4.1. Summary Statistics

We present some findings using figures to help the reader comprehend the trends in the literature. Figure 1 represents the number of manuscripts reviewed by year. The cardinality of research expanded considerably in 2017 and beyond, as indicated in the figure. In Figure 2, the number of forecasting studies is visualized by the output data format (1D, 2D) and year.

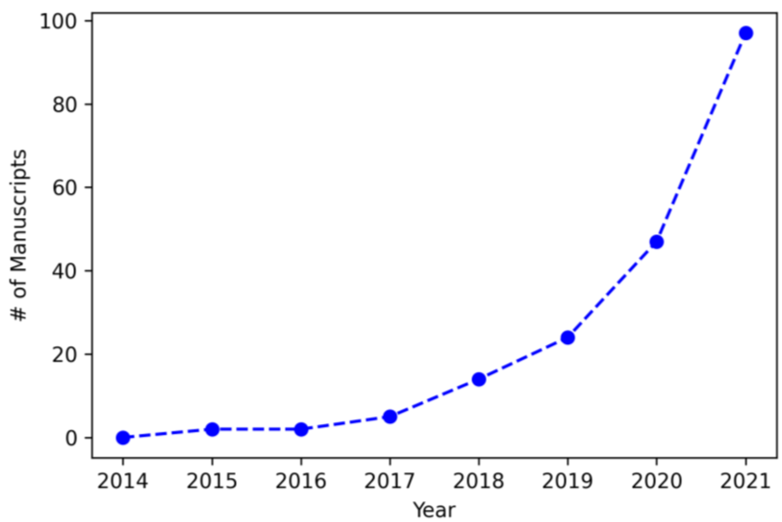

Figure 1. Number of manuscripts by year.

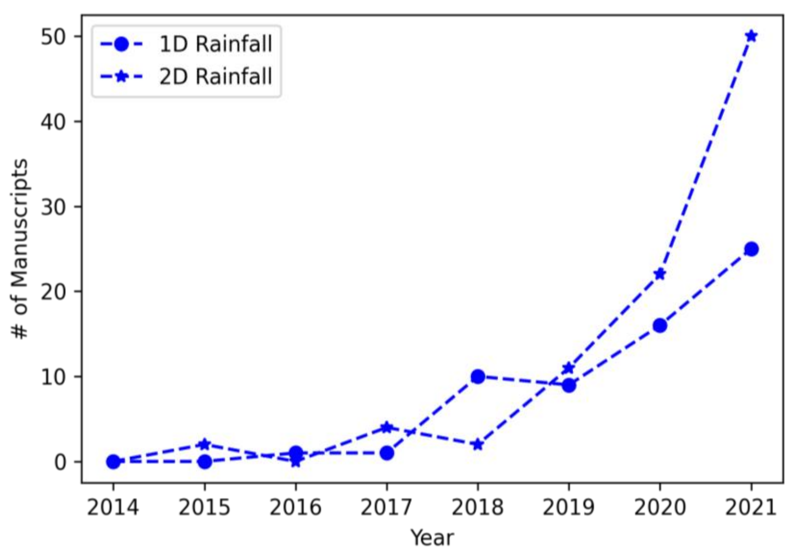

Figure 2. Number of forecasting studies by the used data and year.

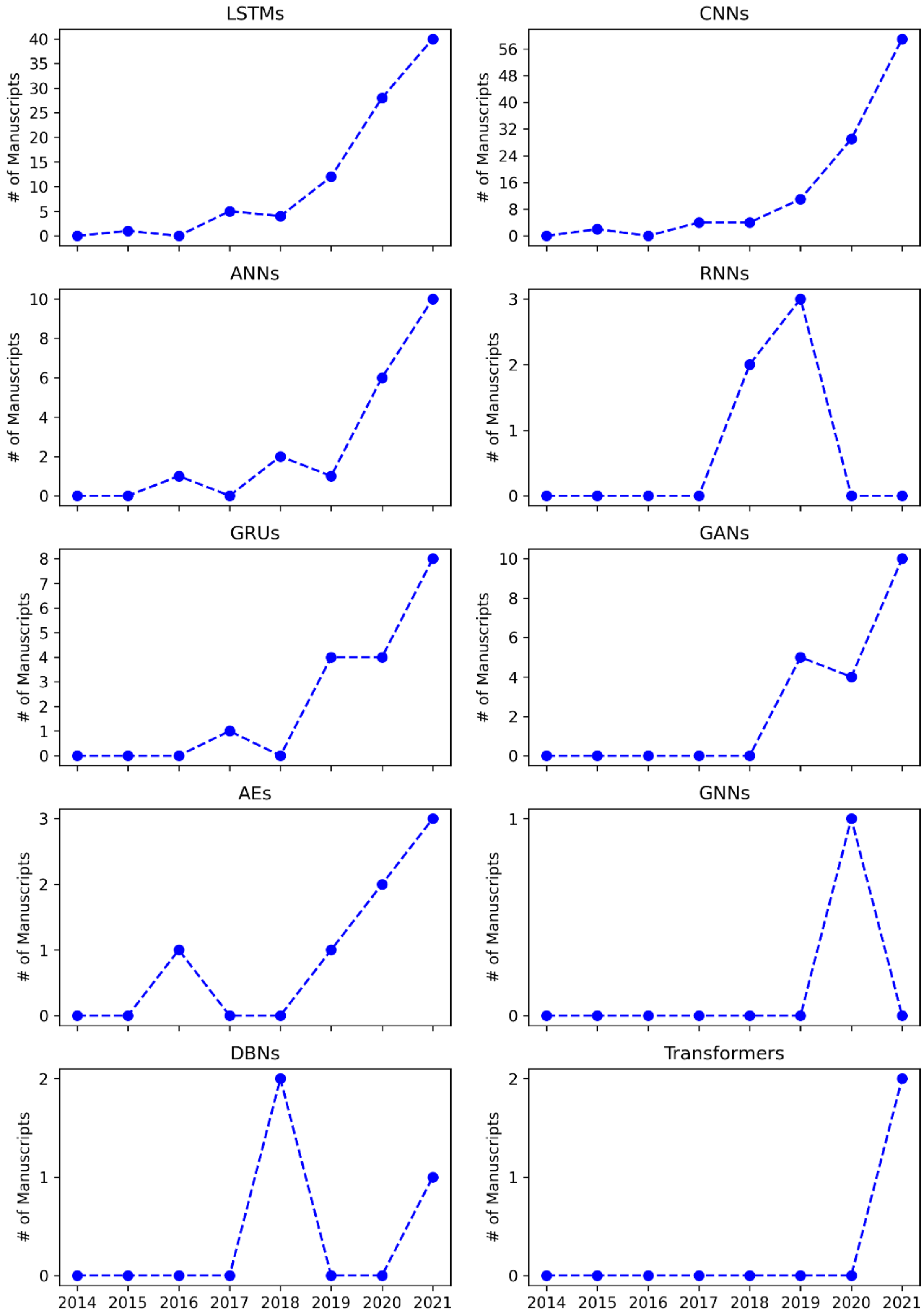

Figure 3. Distribution of architectures used in the studies over the years.

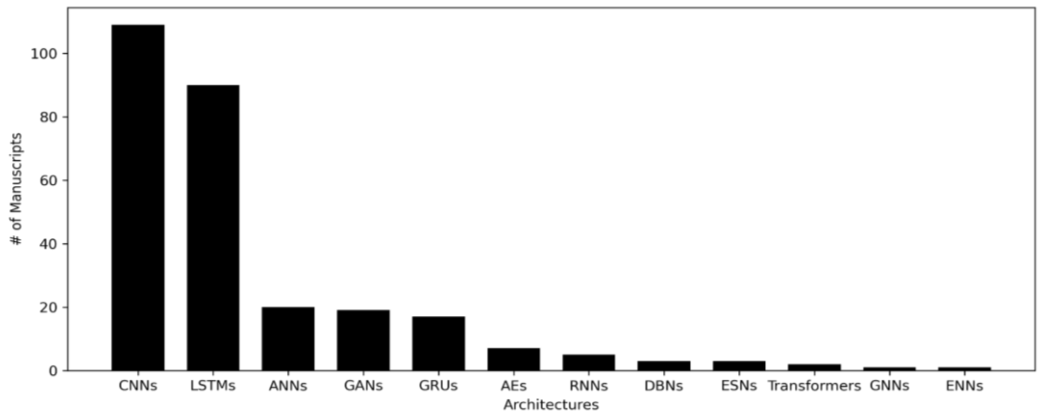

Figure 4. Number of studies used for each of the architectures in the review

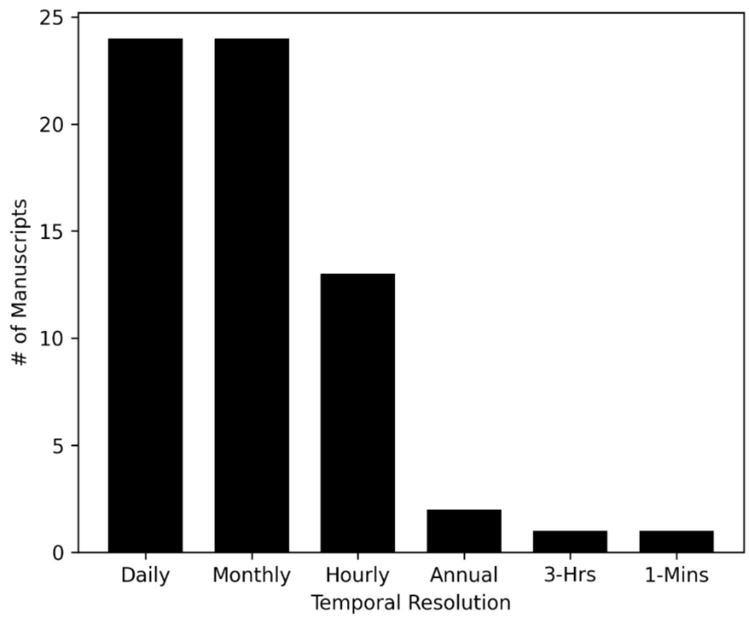

Figure 5. Number of 1D rainfall forecasting studies by the temporal resolution

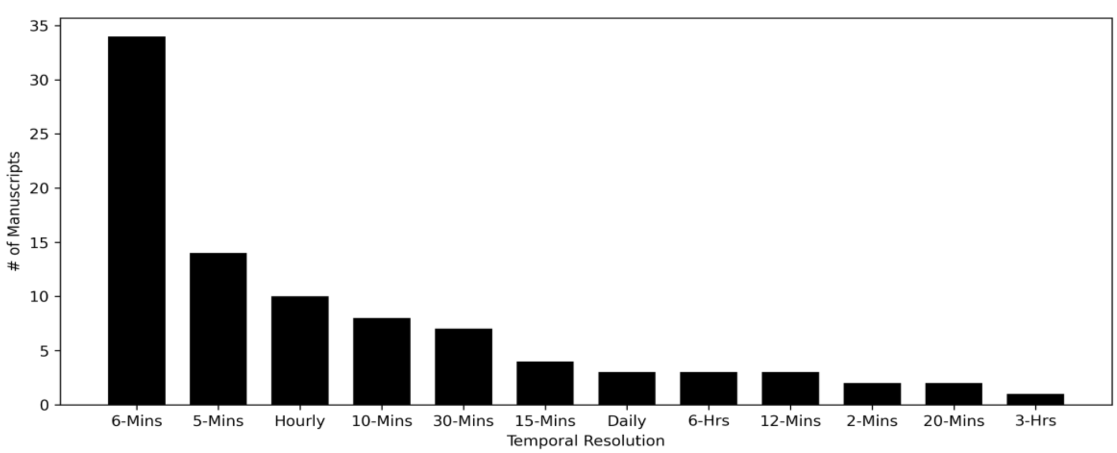

Figure 6. Number of 2D rainfall forecasting studies by the temporal resolution

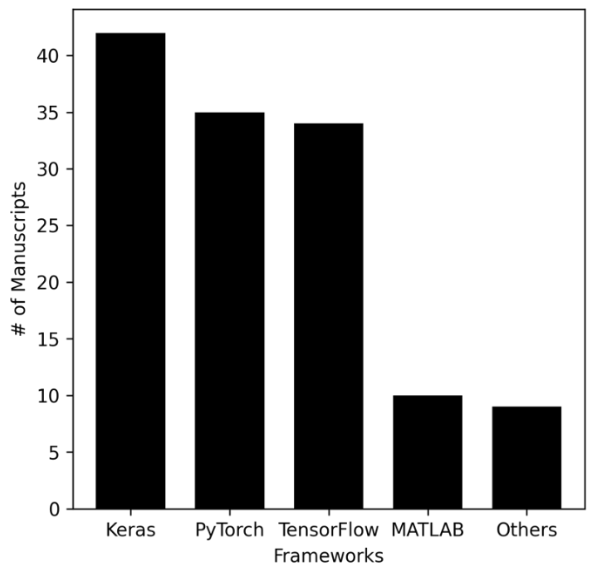

Figure 7. Architectures described in the study and their usage in reviewed papers

Figure 3 illustrates the distribution of the most often used architectures in deep learning across papers and years, while Figure 4 depicts the number of appearances of all architectures in the review. Figures 5 and 6 show the cardinality of the forecasting studies by their temporal resolution to identify the focus of the literature. For 1D rainfall, one can infer that daily forecasting tasks were chosen because forecasting daily values is enough for day-to-day life and environmental monitoring. Hourly does not attract the same attention as it is, most of the time, a harder task to provide precision forecasts for smaller time intervals. When it comes to 2D forecast studies, the main driving factor of the resolution was the temporal resolution of available datasets for radar echo forecasts. Consequently, the lower temporal resolutions (hourly and onwards) were more about actual 2D spatiotemporal forecasts, while radar echo forecasts were mostly covered by higher temporal resolutions (5-minutes, 6-minutes, and so on). Figure 7 provides an overview of how frameworks were used in the manuscripts. The findings indicate that Keras is the most popular framework. Since Keras runs on top of TensorFlow, its actual utilization may be higher because some publications may only mention TensorFlow even when Keras is employed.

4.2. Research Findings

Here, we briefly discuss some of the conclusions drawn from the review as well as highlight certain limitations in the literature. Some of these have already been mentioned in previous reviews as well, such as Sit et al. (2020), so we will reiterate and expand upon them as necessary. Before going into the details, consider the following points as a summary:

- 1D rainfall forecasting has been extensively studied, but without a cumulative approach that would allow academics to build upon one another's work.
- There aren't many datasets on rainfall to help with the preceding point.

- In 2D forecasting, the literature is quite diverse, with many publications that incrementally outperform their predecessors, advancing the field.
- In addition to methods, the definitions of essential topics in deep learning are frequently misinterpreted. Various traditional machine learning algorithms are referred to as "deep learning."
- Some of the publications utilized the words "artificial intelligence" and "deep learning" just to capitalize on the hype surrounding those topics.

1D rainfall forecasting can be categorized into two groups based on the output of the task: single value forecasting and sequence forecasting. When sequences are predicted using historical data, the task becomes more challenging, and making such research rarer in the literature. Another issue with 1D rainfall forecasting is that while many studies have been conducted for various regions of the Earth, it does not lead to developing cumulatively better models. In the literature, similar models for different locations are proposed, but the comparison with previously presented approaches is quite limited. Instead of comparing previously presented approaches, general practice is using other machine learning models for the comparison. This could be the result of the conventional approach of how hydrological modeling is done. Hydrologic models for one area generally perform poorly in other locations because geology, topography, soil, and climate significantly vary between the regions, even when they are geographically adjacent. Models are often optimized for certain regions, which leads performance differences. So, the similar viewpoint among domain scientists may be a crucial point to explain this correlation. Aside from individual efforts, the proposed approaches are rarely reproducible.

However, for 2D rainfall forecasting, the landscape is entirely different. Since extrapolation of 2D sequences is quite a similar task to video frame extrapolation, the literature in computer vision has wide applications in the Earth domain. Having seen some success in video frame extrapolation, many architectures were employed in order to forecast short-term 2D rainfall forecasts as well as radar echo and satellite imagery forecasts. Since the data is different than videos and a different set of physics comes into play (2D vs 3D), various approaches were offered only for the 2D rainfall forecast tasks. Applications of rainfall data beyond forecasting are quite limited. Even though there were some studies that focuses on augmenting datasets by downscaling, also known as super resolution in computer vision literature, the efforts did not stack up to show significant traction while showing great promise. It should be noted that what we referred to as "others" for 2D rainfall section was notably more than "others" for 1D rainfall.

Beyond the studies we have covered in this review, there are certain flaws in the deep learning literature that degrade the quality of research. It is a major problem that among the domain scientists terminology has not been well-established yet. Given that "deep learning" is a relatively new field, it is reasonable that certain terms are used interchangeably. However, there are some manuscripts that claims to present deep learning models, whereas they only employed

SVM from a library or called XGBoost a deep learning algorithm. More examples can be given. So, we couldn't include such manuscripts in this review, even though they claim to be conducting deep learning research. Another problem with the literature is that many studies in the area of deep learning applications research do not offer novelty or contribution in the model set up or algorithm. Publishing a new article while using an algorithm that has been used previously for the same purpose or even for the same data is not helpful and does not exert scientific progress. Nevertheless, a significant number of papers view deep/machine learning algorithms as software packages that take inputs and produce outputs rather than adjusting the algorithm or training method to show greater promise in solving the problem. Quality of the research indicates that some manuscripts were published only due to the hype on deep learning.

In addition to all, it is also worth noting that modeling the environment and earth entails modeling chaos, and chaos occurs quite quickly in Earth data compared to most computer vision tasks. Therefore, when it comes to assessing the methods and their effects, a different set of criteria applies to Earth data. For instance, very complicated network designs that worked successfully in other domains may be ineffective in earth modeling, as noted in some reviewed studies.

4.3. Open Questions

This section will highlight certain open questions and/or application areas where deep learning and its extensions may be useful. We will begin by listing some open questions, like we did with the Research Findings.

- Graph Neural Networks could be used for better earth modeling by considering graph-like the nature of the Earth data.
- Attention mechanisms, particularly transformers, have not been fully employed in rainfall forecasting.
- The state of the art presents a sense of 2D rainfall forecasting, but atmospheric properties change drastically from region to region. Thus, exploring the state of the art in unexplored regions is important for better climate understanding.

GNNs offer an alternative approach for various tasks that use Earth data by utilizing the advantage of the spatial connectivity of numerous data points. Despite the fact that several studies have used them as a proposed methodology or as a method to compare their results, the use of GNNs is very infrequent in the field. As 2D rainfall forecasts already exploit spatial correlations with the convolution process, the applicability of GNNs may be limited to that extent most of the time. However, while most Earth data can be represented with graphs, including 1D rainfall data, it may have more room for improvements on the use of GNNs by investigating their capabilities, even if it does not pass already proposed models by GNNs.

Despite various efforts to augment 1D rainfall data, the full potential of ANNs for enhancing Earth data has not been extensively explored. Since we were only able to find and evaluate a single article that focuses on imputing missing data in hydrologic time series, we feel that more effective methods for missing data imputation could be created. Similarly, the temporal super resolution of atmospheric datasets could be investigated by utilizing the capabilities of recurrent neural network designs in sequential Earth data.

Although several research studies have used attention methods, the use of transformers themselves remains rather rare. Since attention and transformers have fundamentally transformed natural language processing, where the sequential nature of data is just as crucial as time-series data, it should be beneficial to explore temporal attention and transformer in depth, particularly for 1D rainfall. Also, architectures like swin transformers could be utilized in 2D rainfall or radar echo datasets as well.

There are many approaches for 2D rainfall, as we have noted in the Findings subsection. But since meteorological and atmospheric properties change from region to region, it’s not guaranteed to have good results by employing a method that was promising for a particular place on earth. For this very reason, there is still a need for more radar echo products that cover different regions. Consequently, state-of-the-art should be evaluated in those new regions and new methodologies should be devised that works better for new regions and potentially in previously explored regions.

5. Conclusions

This study provides a comprehensive overview of recent deep neural networks on tasks that either improve the quality of the rainfall data or forecast rainfall. In the process, a total of 196 manuscripts were chosen for a thorough evaluation out of 4,876 different manuscripts dated between January 2014 and January 2022 that were systematically gathered using Google Scholar. We believe this study accurately captures the state-of-the-art in general and outlines the literature's strong points and gaps to provide opportunities for both deep learning practitioners and domain scientists. The study shows that the use of deep neural networks is gaining popularity in the field and produces superior outcomes compared to traditional approaches. However, it should be emphasized that the comparisons across previously proposed methods are often limited in the studies, which questions the performance of the models in some ways. As a response, we suggest researchers should make their research open source and accessible on websites like EarthAIHub (Sit and Demir, 2022) or Github with the necessary code and data. Additionally, it is essential to develop or distribute benchmark datasets, much like in other hydrological fields (Sit et al., 2021b; Demir et al., 2022; Newman et al., 2015) or computer vision (Deng et al., 2009; Krizhevsky and Hinton, 2009) and natural language processing (Wang et al., 2018; Rajpurkar et al., 2018).

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Appendix

Table A1. Reviewed papers with curated data points

Papers	Network Type	Open-Source	Reproducible	Dataset	Framework
Agrawal et al., 2019	CNN	No	No	Existing	-
Asanjan et al., 2018	LSTM	No	No	Acquired	-
Aswin et al., 2018	LSTM, CNN	No	No	Acquired	-
Atika et al., 2019	LSTM	No	No	Acquired	-
Ayzel et al., 2019	CNN	No	No	Acquired	Keras, TensorFlow
Ayzel et al., 2020	CNN	Yes	Yes	Acquired	Keras
Babaousmail et al., 2021	CNN, AE	No	No	Acquired	Keras, TensorFlow
Bajpai and Bansal, 2021	CNN, ANN	No	No	Acquired	Keras
Bajpai et al., 2020	CNN	No	No	Acquired	Keras
Baron et al., 2021	CNN, LSTM, GRU	No	No	Acquired	-
Bihlo, 2021	GAN	Yes	Yes	Acquired	Keras
Bojesomo et al., 2021	Transformer	Yes	Yes	Acquired	PyTorch
Bonnet et al., 2020	LSTM	No	No	Existing	-
Cao et al., 2019	RNN	No	No	Acquired	PyTorch
Caraka et al., 2019	LSTM	No	No	Acquired	-
Castro et al., 2021	CNN	Yes	Yes	Acquired	PyTorch
Chai and Goh, 2022	LSTM	No	No	Acquired	-
Chaudhuri and Robertson, 2020	GAN	No	No	Acquired	Python
Chaurasia et al., 2020	LSTM	No	No	Acquired	Python
Chen and Wang, 2021	CNN	No	No	Acquired	PyTorch
Chen et al., 2019	GAN	No	No	Acquired	PyTorch
Chen et al., 2020a	CNN, LSTM	No	No	Acquired	PyTorch

Chen et al., 2020b	CNN, LSTM	No	No	Acquired	TensorFlow
Chen et al., 2021a	GAN, CNN, GRU	No	No	Acquired	PyTorch
Chen et al., 2021b	LSTM, ANN	No	No	Acquired	-
Chen, 2020	CNN, LSTM	No	No	Acquired	PyTorch, TensorFlow
Chhetri et al., 2020	CNN, LSTM, GRU	No	No	Acquired	Keras
Chiu et al., 2021	LSTM, ANN	No	No	Acquired	-
Choi and Kim, 2021	GAN	Yes	Yes	Acquired	Keras
Choi et al., 2021	CNN	Yes	Yes	Acquired	PyTorch
Chong et al., 2020	CNN	No	No	Acquired	-
Civitarese et al., 2021	LSTM, Transformer	No	No	Acquired	-
Cuomo and Chandrasekar, 2021	CNN	No	No	Acquired	PyTorch
da Cunha Mariano, 2020	CNN, LSTM	No	No	Acquired	Keras, TensorFlow
Danpoonkij et al., 2021	CNN	No	No	Acquired	PyTorch
de Ruiter, 2021	CNN	No	No	Acquired	Keras
Du et al., 2018	DBN	No	No	Acquired	Theano
Duong et al., 2018	LSTM	No	No	Acquired	MATLAB
Ehsani et al., 2021	CNN, LSTM	Yes	Yes	Acquired	Keras
Endalie et al., 2022	LSTM	Yes	Yes	Acquired	Keras
Espeholt et al., 2021	CNN, LSTM	No	No	Acquired	-
Fang et al., 2021b	CNN, LSTM	No	No	Acquired	PyTorch
Fernández and Mehrkanoon, 2021	CNN	No	No	Acquired	TensorFlow
Franch et al., 2020	CNN, GRU	No	No	Acquired	Pysteps
G Czibula et al., 2020	ANN	No	No	Acquired	Keras
Gamboa-Villafruela et al., 2021	CNN, LSTM	No	No	Acquired	-
Gao et al., 2021	CNN, LSTM	No	No	Acquired	TensorFlow
Ghazvinian et al., 2021	ANN	No	No	Acquired	Keras, TensorFlow

Gorshenin and Kuzmin, 2018	ANN	No	No	Acquired	Keras
Guevara et al., 2021	GAN, AE	No	No	Acquired	-
Guo et al., 2021	LSTM	No	No	Acquired	PyTorch
Haidar and Verma, 2018	CNN	No	No	Acquired	Keras
Hammad et al., 2021	LSTM, ANN	No	No	Acquired	MATLAB
Hamzah et al., 2021	RNN	No	No	Acquired	-
Haq et al., 2021	LSTM	No	No	Acquired	-
Harsa et al., 2021	ANN	No	No	Acquired	-
Hernández et al., 2016	ANN	No	No	Acquired	-
Hess and Boers, 2021	CNN	No	No	Acquired	-
Hewage et al., 2020	CNN, LSTM	No	No	Acquired	Keras
Hewage et al., 2021	LSTM, CNN	No	No	Acquired	Keras
Heye et al., 2017	CNN, LSTM	No	No	Acquired	-
Hou et al., 2021	LSTM	No	No	Acquired	-
Hsieh et al., 2020	LSTM	No	No	Acquired	-
Hu et al., 2021a	GAN, CNN, LSTM	No	No	Acquired	PyTorch
Hu et al., 2021b	CNN	No	No	Acquired	Keras, TensorFlow
Huang et al., 2021	CNN, RNN	No	No	Acquired	PyTorch
Ionescu et al., 2021	CNN	No	No	Acquired	-
Jing et al., 2019a	CNN, LSTM, GAN	No	No	Acquired	TensorFlow
Jing et al., 2019b	GAN	No	No	Acquired	TensorFlow
Kala et al., 2021	LSTM	No	No	Acquired	-
Kanchan and Shardoor, 2021	ANN, RNN, LSTM	No	No	Acquired	Keras
Kang et al., 2020	LSTM	No	No	Acquired	TensorFlow
Khan and Maity, 2020	CNN, ANN	No	No	Acquired	Keras
Khan et al., 2020	LSTM	No	No	Acquired	PyTorch
Khorrami et al., 2021	CNN	No	No	Existing	-

Kim and Bae, 2017	LSTM	No	No	Acquired	Keras
Kim and Chandrasekar, 2021	CNN, GRU	No	No	Acquired	-
Kim and Hong, 2021	GAN	No	No	Acquired	Keras, TensorFlow
Kim et al., 2017	CNN, LSTM	No	No	Acquired	TensorFlow
Klein et al., 2015	CNN	No	No	Acquired	-
Klocek et al., 2021	CNN, LSTM	No	No	Acquired	-
Kumar et al., 2020	CNN, LSTM	No	No	Existing	-
Kumar et al., 2021	CNN	No	No	Acquired	-
Latifoğlu, 2022	LSTM	No	No	Acquired	-
Le et al., 2020	CNN, AE	No	No	Acquired	Keras
Lee et al., 2020	ANN	No	No	Acquired	-
Leinonen, 2021	CNN, GRU	Yes	Yes	Acquired	Keras, TensorFlow
Lepetit et al., 2021	CNN	No	No	Acquired	-
Li et al., 2019	LSTM	No	No	Acquired	-
Li et al., 2020	CNN	Yes	Yes	Acquired	TensorFlow
Li et al., 2022	CNN	Yes	Yes	Acquired	Keras, TensorFlow
Liu and Lee, 2020	CNN, LSTM, GAN	No	No	Acquired	PyTorch
Llugsi et al., 2020	LSTM	No	No	Acquired	Keras
Lohani, 2019	LSTM	No	No	Acquired	Keras
Luo et al., 2020	LSTM	Yes	Yes	Existing	PyTorch
Luo et al., 2021a	CNN, LSTM	Yes	Yes	Existing	PyTorch
Luo et al., 2021b	CNN	Yes	Yes	Existing	PyTorch
Luo et al., 2022	CNN, LSTM	Yes	Yes	Existing	PyTorch
Ma et al., 2022	GAN	No	No	Acquired	TensorFlow
Mahat et al., 2020	ANN	No	No	Acquired	TensorFlow
Manokij et al., 2019	CNN, GRU	No	No	Acquired	-
Manokij et al., 2021	GRU, CNN	No	No	Acquired	Keras
Marrocu and	GAN	Yes	Yes	Acquired	PyTorch

Massidda, 2020					
Miao et al., 2019	LSTM	No	No	Acquired	TensorFlow
Miao et al., 2020	GNN, LSTM	No	No	Acquired	PyTorch
Misra et al., 2018	LSTM	No	No	Acquired	Theano, Keras
Mitra, 2020	CNN, AE	No	No	Acquired	-
Narejo et al., 2021	DBN, CNN	Yes	Yes	Acquired	MATLAB
Nguyen et al., 2017	CNN, LSTM	No	No	Existing	-
Nguyen et al., 2021	LSTM	No	No	Acquired	TensorFlow
Nie et al., 2021	CNN, LSTM	No	No	Acquired	-
Niu et al., 2020	CNN, LSTM	No	No	Acquired	-
Niu et al., 2021	RNN	No	No	Acquired	PyTorch
Oswalt Manoj and Ananth, 2020	LSTM, CNN	No	No	Acquired	MATLAB
Ouyang and Lu, 2018	ESN	No	No	Acquired	MATLAB
Pan et al., 2021	CNN	No	No	Acquired	-
Ponnoprat, 2021	LSTM, AE	Yes	Yes	Acquired	Keras
Poornima and Pushpalatha, 2019	LSTM, RNN	No	No	Acquired	Keras
Putra et al., 2020	CNN	No	No	Acquired	MATLAB
Ramlan and Mohd Deni, 2021	LSTM, CNN	No	No	Acquired	-
Rasp and Thuerey, 2021	CNN	Yes	Yes	Existing	Keras
Ravuri et al., 2021	GAN	Yes	Yes	Acquired	TensorFlow
Rodrigues et al., 2018	CNN	No	No	Acquired	-
Rosell et al., 2020	ANN	No	No	Acquired	Keras, TensorFlow
Saikhu et al., 2018	RNN	No	No	Acquired	-
Samad et al., 2020	LSTM	No	No	Acquired	-
Samsi et al., 2019	CNN	No	No	Acquired	Keras
Schreurs et al., 2021	GAN	Yes	Yes	Acquired	Keras, TensorFlow

Senekane et al., 2021	RNN, ENN	No	No	Acquired	-
Sha et al., 2020	CNN	No	No	Acquired	-
Shen et al., 2021	CNN, RNN	No	No	Acquired	Python
Shi et al., 2015	CNN, LSTM	Yes	Yes	Existing	Theano
Shi et al., 2017	CNN, LSTM, GRU	No	No	Acquired	-
Shi et al., 2018	CNN, RNN	No	No	Acquired	-
Sit et al., 2021a	CNN	No	No	Existing	PyTorch
Socaci et al., 2020	CNN, LSTM	No	No	Acquired	-
Sønderby et al., 2020	CNN, LSTM	No	No	Acquired	TensorFlow
Soundararajan, 2021	CNN	No	No	Acquired	-
Sugiyarto and Rasjava, 2021	LSTM	No	No	Acquired	-
Sun and Lan, 2021	CNN	No	No	Acquired	Keras
Sun et al., 2021	CNN, GRU	No	No	Acquired	PyTorch
Tao et al., 2016	AE	No	No	Acquired	-
Tao et al., 2021	LSTM	No	No	Acquired	-
Teo, 2019	CNN, LSTM, GRU	No	No	Acquired	Keras
Tian et al., 2019	GAN, CNN, GRU	No	No	Acquired	-
Tosiri et al., 2021	CNN	No	No	Acquired	-
Tran and Song, 2019a	CNN, LSTM, GRU	No	Yes	Existing	TensorFlow
Tran and Song, 2019b	CNN, RNN	No	Yes	Existing	TensorFlow
Trebing et al., 2021	CNN	No	No	Acquired	PyTorch
Tu et al., 2021	CNN	No	No	Acquired	-
van der Kooij, 2021	CNN, RNN	No	No	Acquired	PyTorch
Vandal et al., 2019	AE	No	No	Acquired	-
Venkatesh et al., 2021	GAN, LSTM	No	No	Acquired	-
Wang et al., 2019a	GAN	No	No	Acquired	TensorFlow
Wang et al., 2019b	LSTM	No	No	Acquired	-
Wang et al., 2020	LSTM, ANN	No	No	Acquired	-
Weesakul et al., 2018	ANN	No	No	Acquired	TensorFlow
Weesakul et al., 2021	ANN	No	No	Acquired	TensorFlow
Wei and Hsieh, 2020	CNN, ANN	No	No	Acquired	Keras

Wei and Huang, 2021	CNN	No	Yes	Acquired	Keras
Wei, 2020	CNN	No	No	Acquired	-
Wu et al., 2019	CNN, LSTM, ANN	No	No	Acquired	-
Wu et al., 2021	LSTM	No	No	Acquired	-
Wu, 2019	LSTM, CNN	Yes	Yes	Acquired	Keras
Xie et al., 2020	CNN, GRU	Yes	Yes	Acquired	TensorFlow
Xiong et al., 2021	CNN, LSTM	No	No	Acquired	PyTorch
Xu et al., 2018	ESN	No	No	Acquired	MATLAB
Xu et al., 2021	CNN	Yes	Yes	Acquired	TensorFlow
Xu, 2021	LSTM	No	No	Acquired	TensorFlow
Yadav and Ganguly, 2020	CNN, LSTM	No	No	Acquired	-
Yan et al., 2020	CNN	No	No	Acquired	TensorFlow
Yan et al., 2021	CNN, LSTM	No	No	Acquired	PyTorch
Yao and Chen, 2021	CNN, RNN	No	No	Acquired	-
Yao et al., 2020	LSTM, GAN	No	No	Acquired	-
Yasuno et al., 2021	CNN, LSTM	No	No	Acquired	Keras
Yen et al., 2019	ESN	No	No	Acquired	MATLAB
Yin et al., 2021a	CNN, GRU	No	No	Existing	-
Yin et al., 2021b	ANN	No	No	Acquired	-
Yuan et al., 2021	CNN	No	No	Acquired	PyTorch
Zhang et al., 2018	DBN	No	No	Acquired	MATLAB
Zhang et al., 2020a	CNN, LSTM	No	No	Existing	-
Zhang et al., 2020b	LSTM	No	No	Acquired	Python
Zhang et al., 2021a	CNN, LSTM	No	No	Acquired	PyTorch
Zhang et al., 2021b	CNN, GRU	No	No	Acquired	PyTorch
Zhang et al., 2021c	LSTM	No	No	Acquired	-
Zhang et al., 2021d	CNN, LSTM	No	Yes	Existing	Python
Zhao et al., 2021	CNN	No	No	Acquired	-
Zhong et al., 2020	CNN, LSTM, GRU	Yes	Yes	Existing	PyTorch