A systematic review on sequence-to-sequence learning with neural network and its models

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ABSTRACT

We develop a precise writing survey on sequence-to-sequence learning with neural network and its models. The primary aim of this report is to enhance the knowledge of the sequence-to-sequence neural network and to locate the best way to deal with executing it. Three models are mostly used in sequence-to-sequence neural network applications, namely: recurrent neural networks (RNN), connectionist temporal classification (CTC), and attention model. The evidence we adopted in conducting this survey included utilizing the examination inquiries or research questions to determine keywords, which were used to search for bits of peer-reviewed papers, articles, or books at scholastic directories. Through introductory hunts, 790 papers, and scholarly works were found, and with the assistance of choice criteria and PRISMA methodology, the number of papers reviewed decreased to 16. Every one of the 16 articles was categorized by their contribution to each examination question, and they were broken down. At last, the examination papers experienced a quality appraisal where the subsequent range was from 83.3% to 100%. The proposed systematic review enabled us to collect, evaluate, analyze, and explore different approaches of implementing sequence-to-sequence neural network models and pointed out the most common use in machine learning. We followed a methodology that shows the potential of applying these models to real-world applications.

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1. INTRODUCTION

Machine learning (ML) is a logical investigation of calculations and accurate models within computational frameworks that act without utilizing clear guidelines, depending on examples and surmising. It is viewed as a subset of computerized reasoning [1-4]. Performing ML includes making a model, which is prepared on some preparation information and afterward can process extra information to make forecasts [5-7]. Different kinds of models have been utilized and investigated for ML frameworks. These models include neural networks, decision trees, regression analysis and have a massive application that includes speech and object recognition [8-15]. The scope of this paper is focused on neural networks and their subsets, particularly neural networks and sequence-to-sequence learning. Neural systems or connectionist frameworks are registering frameworks dubiously motivated by the organic neural systems that establish creature cerebrums. Such frameworks "learn" to perform assignments by thinking about models, for the most part,

without being modified with task-explicit guidelines. Their applications are massive, and they have been developed to perform many difficult tasks, mainly including prediction and classification [16].

Sequence-to-Sequence learning is a part of ML and a method of neural networks that is mostly utilized in language processing models [17-23]. It can be implemented with recurrent neural networks (RNNs) using encoder-decoder based machine interpretation that maps an input sequence to a yield of a succession of output sequence with a tag and consideration esteem. The idea is to exploit two RNN that will cooperate with a unique token and attempt to anticipate the following state arrangement from the past succession. Sequence-to-Sequence models can also be implemented through what is known as connectionist temporal classification (CTC) and attention-based models. The sequence-to-sequence model was initially created by Google for machine translation and was introduced to train the model with a single command. The model was also made to be easily reproducible and extendable such that the code files were organized in a measured manner and that simple to expand upon and recreate.

The extent of this paper incorporates neural systems and their subsets, especially recurrent neural networks (RNN), connectionist temporal classification (CTC), and attention-based models to determine which is the best-suited approach to implement with sequence-to-sequence learning. This paper aims to explore the working of sequence-to-sequence learning and their different applications, which is reflected in the research questions of the paper.

This paper will conduct a systematic literature review on sequence-to-sequence neural network through exploring different academic research directories to look for peer-reviewed content. More on the method of conducting this systematic literature review is discussed in Section 3. The structure of this paper is as: Section 2 will talk about and dissect the accessible writing about RNNs, CTC, and attention-based models learning; it will explain the working of each network and discuss their strengths and weaknesses. Section 3 will study the examination methodology used to lead the systematic literature review, which incorporates the detailing and formulation of the research questions. Section 4 will utilize the academic writings to conduct a quality assessment, respond to the questions addressed, and lastly, section 5 will have a short conclusion to the paper.

2. LITERATURE REVIEW

Neural networks is an established model of machine learning and has had extensive research done on it over the years; Sequence-to-sequence neural network is a new learning technique [9, 24, 25]. Despite this, there is still quite a substantial some of research done on both models and techniques, which will be expanded on in this section.

2.1. Background

Neural networks are inspired by biological neural networks systems that comprise animals' brains; they are designed to develop, progress, and solve complex problems that require a high level of comprehension to perform. There are many types of neural networks that are found to perform extremely well with such difficult tasks such as speech recognition and machine translation; one of such networks are the recurrent neural networks (RNN). The working principle behind RNNs is essentially constructed around neural network models that incorporate an encoder-decoder framework that can be used and trained end-to-end to map input sequences into output target sequences [26]. A wide-ranging definition of sequence-to-sequence models can be said to "refers to the broader class of models that include all models that map one sequence to another" [27]. Thus, by comparing it to the definition of [26], it is clear to see the relation between the two definitions.

Connectionist temporal classifications (CTC) is a kind of neural system yield related to scoring capacity, for preparing intermittent neural systems to handle grouping issues where the timing is variable. It may be utilized for assignments like online penmanship recognition or perceiving phonemes in discourse sound. CTC was presented in 2006 and alluded to the yields and scoring and is autonomous of the hidden neural system structure [28]. Historically, CTC has been used for the classification of unsegmented sequences with RNNs, such as cases of handwriting or speech recognition. RNNs on their own were not sufficient for the task as their standard neural system target capacities are characterized independently for each point in the preparation arrangement; basically, RNNs must be prepared to make a progression of autonomous mark orders.

In order to remove this dependency and enable RNNs to perform this task, the network had to decode the system outputs as a likelihood appropriation over all possible mark successions, adapted on a given input grouping. Given this dispersion, a target capacity can be determined that straightforwardly expands the probabilities of the right marking. Since the target work is differentiable, the system would then

be able to be prepared with standard backpropagation through time [29]. Thus, using this concept, therefore, use of RNNs in this way was known as CTC.

The attention mechanism is a type of neural network that allows the decoder aspect of the network to focus on certain parts of the sequence while the output is generated. Attention-based models help remove any dependencies on variable-length inputs without compressing them into fixed vectors by using variable-length memory where then, the model is free to use this memory in a truly adaptable way to create the output succession. In addition, various pieces of memory can be obtained at multiple yield time steps. These models are well-persuaded in light of the fact that data is lost by compacting long factor length groupings into a fixed-size vector, and choosing the pressure is an extra assignment to comprehend [30].

2.2. Sequence-to-sequence models

There are several approaches used to implement sequence-to-sequence algorithm models. The most common models are the connectionist temporal classification (CTC), RNNs, and attention-based model.

2.2.1. Connectionist temporal classification

The CTC algorithm proposed by [28]. This algorithm is a method of preparing start to finish models without a requirement of casing level arrangement of the objective names for a preparation articulation. CTC defines the probability of the output condition, estimated to use recurrent neural networks, simply known as encoders [31]. In addition, CTC uses for sequence-to-sequence method to help to address any issues related to the length of the output labels when it is shorter than the length of the input sequence since "CTC introduces a special blank label and allows for repetition of labels to force the output and input sequences to have the same length. CTC outputs are usually dominated by blank symbols" [32]. This gives CTC a major advantage when using sequence-to-sequence models in many applications such as translation.

2.2.2. Recurrent neural networks

The idea behind sequence-to-sequence models using the RNN approach utilizes two RNN that will cooperate with a unique token and attempt to anticipate the following state arrangement from the past succession. The RNN transducer differs on the encoder usage from the CTC alignment model by different repeat lease expectation arrangement over the output sequences. Instinctively, the encoder can be thought of as an acoustic model, while the expectation arranges practically equivalent to a language model. The expectation arrange gets as info and processes an output vector, subject to the whole sequence of labels [31].

2.2.3. Attention model

It is a consideration-based model contains an encoder organize, as in the RNN transducer model. In any case, in contrast to the RNN transducer, in which the encoder and the expectation arrange are displayed autonomously and consolidated in the joint system, a consideration based model uses a solitary decoder to deliver an appropriation over the marks molded on the full grouping of past forecasts and the acoustics [31]. The decoder network consists of several recurrent layers. The attention aspect of the model puts a higher weight on certain layers to produce an output using the end-to-end sequence method.

3. METHODOLOGY

The principle of research methodology is developed based on a systematic literature review. The paper follows the systematic review methodology illustrated by [33] to direct the deliberate literature audit. The reason for selecting the systematic review for sequence-to-sequence neural network is that no systematic review focuses on sequence-to-sequence neural network usage, limitations, and applications. Moreover, this methodology enabled us to collect, evaluate, analyze, and explore different approaches to implementing sequence-to-sequence neural network models and find the most common use in machine learning. The initial step to this method is to figure out the research hypothesis of our paper.

3.1. Research hypothesis

The research hypothesis developed for the paper were as:

- 1. What are the different applications of sequence-to-sequence neural network models?
- 2. How has this model been implemented and developed?
- 3. What are the advantages and limitations of implementing sequence-to-sequence models?
- 4. What is the best model to approach sequence-to-sequence implementation?
- 5. What are the countries that contributed to the development and implementation of sequence-to-sequence? Table 1 shows the research hypothesis, including their motivation.

	1 401	e 1. Research motivation and hypothesis
RQ#	Research Hypothesis	Motivation
RQ1	What are the different	This question helps gain a broader understanding of all the applications of sequence-
	applications of sequence-to- sequence models?	to-sequence models to relieve a lot of ambiguity surrounding the definition. This will later help identify the best possible approach to implement the model based on the
		best advantages it has on each application.
RQ2	How has this model been	This question allows a deeper understanding of the development of the model.
	implemented and developed?	Moreover, It will highlight its shortcomings to identify the additional work needs to be done on the field and what is the best and least problematic approach to be used with common machine learning applications like speech recognition and translation.
RQ3	What are the advantages and	This question addresses the significance of the model and how the installation has
	limitations of implementing	helped in relieving some of the problems that were involved in the field of machine
	sequence-to-sequence models?	learning prior to its development. Moreover, this helps to highlight some challenges that are still not solved and new challenges that developed with the new model.
RQ4	What is the best model to	This question will highlight the advantages and disadvantages of every approach. It
	approach sequence-to-sequence implementation?	will help choose the best approach for the purposes of suggesting a standard to use when implementing this model in common machine learning applications.
RQ5	What are the countries that	This question will highlight the most countries contributed to the implementation and
	contributed to the development	development Sequence-to-Sequence
	and implementation of sequence-	
	to-sequence?	

Table 1. Research motivation and hypothesis

3.2. Research strategy

The principle of research strategy in this paper is to conduct a careful checking on the subsequent database, peer-reviewed journals, and periodicals. Most of the papers utilized from arXiv, Google Scholar, Science Direct, IEEE Xplore, and Springer complete journals. When the most significant research registries were chosen, important keywords retrieved from the research hypothesis were utilized in search through pertinent titles and modified works of papers and articles. A Boolean technique adapted to string together the important search terms to locate the most significant peer-evaluated items for this paper. Specific perspectives were viewed when utilizing the search terms, such as equivalent words or plurals of terms. Table 2 shows the search terms used in various databases and the outcomes it accomplished. Overall, there were 871 papers appeared through the initial searching stage. From those, 86 papers appeared to be duplicated, and five papers were found through citations of found academic papers, which brough the total number of papers to 790. These papers were refined. The final pieces of literature used in this paper were screening according to the selection criteria and the preferred reporting items for systematic reviews and meta-analyses (PRISMA) Statement [34]. Figure 1 shows the PRISMA flowchart.

Table 2. Boolean technique search results

Database	Search String	Number of results
Google Scholar	("Connectionist temporal classifications") and ("sequence-to-sequence") and	56
	("RNN") and ("CTC")	
Science Direct	(("Attention model" or "attention mechanism") and ("sequence-to-Sequence"))	68
IEEE Xplore	"Sequence-to-sequence" and "neural network" and "challenges" or "limitation"	284
Springer Complete Journals	("Sequence-to-sequence") and ("recurrent neural networks" or "connectionist	463
•	temporal classifications" or "attention model")	

3.3. Inclusion and exclusion criteria

Inclusion and exclusion criteria were chosen criteria to measure the most formal writing for the extent of this paper. In view of these criteria, the papers which followed the research perspective criteria were included for the extent of research. Table 3 shows the inclusion and exclusion criteria.

Inclusion criteria	Excision criteria
Must be peer-reviewed journal papers, articles, or books	Articles are written in another language
Should include the development and implementation of the	Papers focus on specialized parts or working the sequence-to-
sequence-to-sequence model and neural networks	sequence model and neural network
Must be written in English	Discuses as a subtopic in Sequence-to-Sequence, RNN, CTC,
-	and attention models.

Academic papers that failed to meet the mentioned criteria were excluded from research. The initial screening was done on all the extracted 790 records in order to narrow the result. These records were

compared against pre-selection criteria that included refining the search fields to engineering and computer science, limiting the results to the no older than ten years. This resulted in the evaluated numbers to decrease to 413 papers, which were assessed by the selection criteria mentioned. Figure 1 represents the process for both the pre-selection and the selection criteria. This process resulted in 16 papers to be included in the systematic review in sequence-to-sequence neural network.



Figure 1. PRISMA flowchart

3.4. Quality assessment

Inclusion quality assessment is one of the most essential and critical parts of any systematic review [35-39]. The assessment quality assurance checklist for our systematic review consists of 6 questions for the 16 chosen papers, as shown in Table 4. The scoring of this process is done based on the work of [40] as: a 'Yes' to the question of the quality assessment is indicated by a 1, a 'No' was indicated by a 0, and a 'Partially' was indicated by a 0.5. As seen by the results in Table 5, all the chosen papers have passed the quality assessment.

Ques.Quality Assurance Question1Are the research aims specified clearly?2Is the information presented clear and concise?3Does the study provide enough explanation of its methodology?4Do the findings of the study add to the understanding of sequence-to-sequence models?5Are the conclusions clearly identified?6Are the conclusions logical and concise with the flow of the paper?		Table 4. Quality assurance questions
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 Is the information presented clear and concise? Does the study provide enough explanation of its methodology? Do the findings of the study add to the understanding of sequence-to-sequence models? Are the conclusions clearly identified? Are the conclusions logical and concise with the flow of the paper? 	1	Are the research aims specified clearly?
 Does the study provide enough explanation of its methodology? Do the findings of the study add to the understanding of sequence-to-sequence models? Are the conclusions clearly identified? Are the conclusions logical and concise with the flow of the paper? 	2	Is the information presented clear and concise?
 4 Do the findings of the study add to the understanding of sequence-to-sequence models? 5 Are the conclusions clearly identified? 6 Are the conclusions logical and concise with the flow of the paper? 	3	Does the study provide enough explanation of its methodology?
5 Are the conclusions clearly identified?6 Are the conclusions logical and concise with the flow of the paper?	4	Do the findings of the study add to the understanding of sequence-to-sequence models?
6 Are the conclusions logical and concise with the flow of the paper?	5	Are the conclusions clearly identified?
	6	Are the conclusions logical and concise with the flow of the paper?

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Table 5. Quality assessment results								
Study	Q1	Q2	Q3	Q4	Q5	Q6	Total	Percentage
S1	1	1	0.5	1	1	1	5.5	91.67%
S2	1	1	1	1	0.5	1	5.5	91.67%
S 3	1	1	1	0	1	1	5	83.33%
S 4	1	1	1	0.5	1	0.5	5	83.33%
S5	1	1	1	0.5	1	1	5.5	91.67%
S6	1	1	0.5	0.5	1	1	5	83.33%
S7	1	1	1	1	1	1	6	100%
S 8	1	1	0.5	1	1	0.5	5	83.33%
S9	1	1	1	0	1	1	5	83.33%
S10	1	1	1	0	1	1	5	83.33%
S11	1	1	1	1	1	1	6	100%
S12	1	1	1	1	0.5	1	5.5	91.67%
S13	1	1	0.5	1	0.5	1	5.5	91.67%
S14	1	0.5	1	0.5	1	1	5.5	91.67%
S15	1	1	0	1	1	1	5	83.33%
S16	1	1	1	1	1	0.5	5.5	91.67%

4. RESULTS AND DISCUSSION

Utilizing the research procedure outlined in the previous section, the research questions that were tended to each paper are classified and analyzed based on their contribution to each question.

4.1. Classifications and analysis of studies

By studying all the 16 research papers included in the systematic review, a classification system was comprised based on their contribution to answering the research questions. Markings were made if the main focus of the paper was related to a particular category. Most papers, for example, talked in brief about the different applications of sequence-to-sequence (seq2seq) models. However, only studies that were mainly focused on a certain application or discussed several applications in depth were categorized as 'Applications of seq2seq'. The classification results can be seen in Table 6. Additionally, each study was analyzed in detail, and the results of this detailed study are outlined in Table 7 (see in Appendix). Figure 2 shows the publication distributions country wise. As the results show, there has been an increase in interest in this topic over the last two decades, as indicated by the increase in a number of publications since 1990. Most of this research is focused on the US, as mentioned.



Figure 2. Publication distribution country wise

4.2. Quality assessment results

Using the questions outlined in Table 4, a score was given to each of the 16 studies used in this paper. The maximum score that a paper can have is 6. The results of each paper are presented in Table 6.

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	Table 6. Classification of literature review					
Study	Source	Applications	Seq2seq via	Seq2seq	Seq2seq via	Challenges of
		of seq2seq	RNN	via CTC	attention models	seq2seq
S1	[41]	х	х			
S2	[32]			х	Х	
S 3	[28]		х	х		Х
S4	[42]	Х		х		
S5	[43]	х	х			
S6	[27]	х				Х
S 7	[16]	х	х			Х
S 8	[31]		х	х	Х	
S9	[26]		х	х		
S10	[44]			х		
S11	[45]	Х			Х	
S12	[8]	х	х			
S13	[46]	Х	х			
S14	[29]	х				Х
S15	[47]	х	х			
S16	[48]	х	х			

4.3. Answers to research questions

RQ1. What are the different applications of the sequence-to-sequence neural network model? a.

As seen from Error! Reference source not found., 11, or 68.75%, of the studies were relevant to the applications of sequence-to-sequence neural network models, indicating not only the relevance of this question but also its widespread interest in the field. The general consensus was that sequence-to-sequence models were best utilized for speech recognition and general linguistics, as suggested by [16, 31, 48]. In addition, sequence-to-sequence models can be used for video to text conversion [46] and handling large vocabularies, optimizing translation performance, and multi-lingual learning [27].

h. RQ2. How has this model been implemented and developed?

All 16 of the papers used in the systematic review mentioned different approaches to implementing and developing the sequence-to-sequence neural network models. For example: R. Prabhavalkar et al. [31] summarises three methods of implementation, which include: RNNs, Connectionist Temporal Classifications (CTC), and Attention models.

RQ3. What are the advantages and limitations of implementing sequence-to-sequence models? С

I. Sutskever et al. [8] and Y. H. Chan et al. [41] talked mostly about implementations using RNNs and discussed many advantages and disadvantages of applying this model, while in [28, 42] discussed the implementation through CTC in details with the limitations in implementation. Similarly, in [32, 45] discussed the limitations of the attention model.

RQ4. What is the best model to approach sequence-to-sequence implementation? d

The majority of the papers (62.5%) talk about RNNs and their implementation, limitations, and endorsement. Notably, the work of [31] compared the three different approaches and found the most promising approach to be "the RNN transducer, attention-based models, and a novel RNN transducer augmented with attention."

5. CONCLUSION

In conclusion, the paper aimed to conduct a systematic review on the topic of the sequence-tosequence neural network and its models. The main aim of the review to gain insight into the sequence-tosequence neural network models and to find the best approach to implement it. Three such approaches were found: through recurrent neural networks, connectionist temporal classifications (CTC), and attention models. The research question derived for the literature review were encompassing the applications of sequence-to-sequence models, their advantages and disadvantages, as well as the best implementation approach for them. The procedure done to conduct this systematic literature review included using the research questions to derive keywords that were then used to look at the subsequent database, peer-reviewed journals, and periodicals. Most of papers utilized from arXiv, Google Scholar, Science Direct, IEEE Xplore and Springer complete journals. Through initial searches, 790 papers and academic works were found, and with the help of selection criteria and PRISMA procedure, the number of papers reviewed in this paper was reduced to 16. Each of the 16 papers was categorized by their contribution to each research question, and they were analyzed. Finally, the research papers underwent a quality assessment where the resulting range was from 83.3% to 100%.

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Table /	Analysi	a of the	liferature	review
rable /.	. 1 Milai y 51	s or the	merature	10 10 10 10

C 4 1	C	Promoso	ysis of the fit	Detabase	Ein din
Study	Source	Purpose	Country	Database	Findings
51	[41]	The authors suggested and	Hong Kong	IEEE	Different methods were tested on
		experimented with an alternative		Xplore	emotional encoding information for
		approach to embedded emotional			sequence to sequence generation
		information at the encoder stage			response and evaluated the result, which
		of sequence to sequence based			was found to have a positive effect on a
		emotional generation.			sentence level.
S2	[32]	The paper proposed a new	Canada	IEEE	The proposed method boosted the end-to-
		method used in neural speech		Xplore	end acoustic-to-word CTC model and
		recognition by aligning the		1	achieved better WER than the traditional
		attention modeling within the			context-dependent phoneme CTC model
		CTC framework			decoded with a very large-sized language
		ere hanework			model
\$3	[28]	The paper presented a novel	Switzerland	ACM	The method is derived from probabilistic
35	[20]	method for training PNNs to	Switzerland	Digital	principles and fits the framework of the
		label unsegmented acquerees		Librarias	principles and his the framework of the
		label unsegnented sequences.		Libraries	neural network classifier. It allows the
		An experiment on the HMH			network to be trained directly for
		speech corpus demonstrates its			sequence labeling by removing the
		advantages over both a baseline			requirement of pre-segmented data.
		HMM and a hybrid HMM-RNN".			
S 4	[42]	The authors developed a	USA	IEEE	The paper developed a streaming
		technique to base the RNN-T		Xplore	keyword by using (RNN-T) model to
		system towards a specific			predict either phonemes or graphemes as
		keyword.			sub-word, which allows detecting random
					expressions.
S5	[43]	The authors proposed an artificial	Bangladesh	Science	The paper worked with RNN structures and
		Bangla text generator with		Direct	LTSM networks to be able to fulfill their
		LSTM and model it to validate			purpose. They were able to "model for
		the accuracy of the text			achieving multi-task sequence to sequence
		generators.			text generation and multi-way translation like
		8			Bengali articles, caption generation"
S 6	[27]	The author introduced 'neural	USA	arXiv	The paper covered the basics of neural
50	[27]	machine translation' or 'neural	USA	arzarv	machine translation and sequence to
		machine translation of neural			machine translation and sequence to
		sequence-to-sequence models			application such as Handling large
					application such as Handling large
					vocabularies, Optimizing translation
~-			.	a .	performance, and Multi-lingual learning.
S7	[16]	This paper carries out a	India	Science	"Neural networks are being used in areas
		comprehensive review of articles		Direct	of prediction and classification, the areas
		that involve a comparative study			where statistical methods have
		of feed forward neural networks			traditionally been used".
		and statistical techniques used for			"One of the important advantages of
		prediction and classification			neural networks cited in the literature is
		problems in various areas of			that it can automatically approximate any
		applications. Tabular presentations			nonlinear mathematical function".
		highlighting the important features			
		of these articles are also provided			
S 8	[31]	The authors conducted a detailed	USA	Google	"[they] compared a number of sequence-
		evaluation of sequence to		Scholar	to-sequence modeling approaches on an
		sequence models which are used in			LVCSR task. In experimental
		the task of speech recognition such			evaluations, we find that the RNN
		as connectionist temporal			transducer attention-based models and a
		classification (CTC) the recurrent			novel RNN transducer augmented with
		neural network (DNN)			attention are comparable in performance
		transducer an attention based			to a strong state of the art baseling or a
		model and a model which			dictation test set even when eveluated
		augments the DNN transderer			without the use of an external manunci-ti
		augments the KINN transducer			without the use of an external pronunciation
50	[20]	"We introduce an angle 1	LIC A	Dagarat	UT anguage model
39	[20]	we introduce an encoder-	USA	Research	we presented the RINA model, which is
		decoder recurrent neural network		Gate	a recurrent neural network model in the
		model called recurrent neural			encoder-decoder framework. We applied
		aligner (RNA) that can be used for			it to end-to-end speech recognition and
		the sequence to sequence mapping			showed initial experimental results on
		tasks. Like connectionist temporal			YouTube transcription and mobile dictation
		classification (CTC) models, RNA			tasks. We found that the RNA grapheme
		defines a probability distribution			model can not perform as well as CTC
		over target label sequences,			CD phone models for mobile dictation
		including blank labels			task where the vocabulary size is larger,
		corresponding to each time step			and the training data is relatively smaller."
		in the input".			
		A			

Study	Source	Purpose	Country	Database	Findings
S10	[44]	"We propose SAN-CTC, a deep, fully self-attentional network for CTC, and show it is tractable and competitive for end-to-end speech recognition. We motivate the architecture for speech, evaluate the position and down-sampling approaches, and explore how to label alphabets (character, phoneme, subword) affect attention heads and performance".	UK	IEEE Xplore	"SAN-CTC trains quickly and outperforms existing CTC models and most encoder-decoder models, with character error rates (CERs) of 4.7% in 1 day on WSJ eval92 and 2.8% in 1 week on LibriSpeech test-clean, with a fixed architecture and one GPU. Similar improvements hold for WERs after LM decoding.
S11	[45]	The work is focused on using sequence to sequence the attention model by the Google brain team to generate the abstract of research papers. Moreover, temporal attention mechanism has been used in replacement to the global attention to cater to the problem of repetitive words.	Pakistan	IEEE Xplore	The result indicates that the temporal attention model is a useful method for generating summaries. Moreover, results indicate that with the increase in dataset size, the accuracy of the results also increases.
S12	[8]	The paper uses a multilayered long short-term memory (LSTM) to map the input sequence to a vector of fixed dimensionality. Then, another deep LSTM to decode the target sequence from the vector."	Canada	Google Scholar	The main result is that on an English to French translation task from the WMT- 14 dataset, the translations produced by the LSTM achieve a BLEU score of 34.8 on the entire test set, where the LSTM's BLEU score was penalized on out-of-vocabulary words. Additionally, the LSTM did not have difficulty in long sentences
S13	[46]	"We propose a novel end-to-end sequence-to-sequence model to generate captions for videos. For this, we exploit recurrent neural net- works, specifically LSTMs, which have demonstrated state-of- the-art performance in image caption generation."	USA	IEEE Xplore	[This paper] constructed descriptions using a sequence to sequence model, where frames are first to read sequentially, and then words are generated sequentially. This allows us to handle variable-length input and output while simultaneously modeling temporal structure. Our model achieves state-of- the-art performance on the MSVD dataset, and outperforms related work on two large and challenging movie-description datasets."
S14	[29]	"Basic backpropagation, which is a simple method now being widely used in areas like pattern recognition and fault diagnosis, is reviewed. The basic equations for backpropagation through time, and applications to areas like pattern recognition involving dynamic systems, systems identification, and control are discussed."	USA	IEEE Xplore	This paper presents the key equations of backpropagation, as applied to neural networks of varying degrees of complexity. It has also discussed other papers which elaborate on the extensions of this method to more general applications and some of the tradeoffs involved
S15	[47]	"This paper examines the most popular DNNs approaches: LSTM, Encoder-Decoder network and Memory network in sequence prediction field to handle the software sequence learning and prediction task."	China	IEEE Xplore	"Our results demonstrate that attention mechanism does not fit all seq2seq problems, especially in a weak mapping relationship. And additional information can benefit sequence prediction in neural networks."
S16	[48]	The paper presented a character level sequence to sequence the learning method. The author set in an RNN into an encoder-decoder framework and generate the character-level sequence in representation as an input	China	IEEE Xplore	Experimental results by the authors confirmed that the proposed approach achieved performance close to conventional word and phrase-based translation systems. The proposed methods allows to "reads quantized characters into the translation system, instead of using a predefined vocabulary with a limited number of words"

Table 7. Analysis of the literature review (*Continue*)

A systematic review on sequence-to-sequence learning with neural network and its models (Hana Yousuf)

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