Software Engineering Meets Deep Learning: 
A Literature Review

Fabio Ferreira\textsuperscript{1,2}, Luciana Lourdes Silva\textsuperscript{3}, and Marco Tulio Valente\textsuperscript{1}

\textsuperscript{1}Department of Computer Science, UFMG, Brazil
\textsuperscript{2}Federal Institute of the Southeast of Minas Gerais - Campus Barbacena, Brazil
\textsuperscript{3}Federal Institute of Minas Gerais - Campus Ouro Branco, Brazil

Abstract

Deep learning (DL) is being used nowadays in many traditional software engineering (SE) problems and tasks, such as software documentation, defect prediction, and software testing. However, since the renaissance of DL techniques is still very recent, we lack works that summarize and condense the most recent and relevant research conducted in the intersection of DL and SE. Therefore, in this paper we describe the first results of a literature review covering 81 papers about DL & SE.

1 Introduction

Deep learning (DL) applications are increasingly important in many areas, such as automatic text translation \cite{1}, image recognition \cite{2,3}, self-driving cars \cite{4,5}, smart cities \cite{6,7}, etc. Furthermore, various frameworks—such as TensorFlow\textsuperscript{1} and PyTorch\textsuperscript{2}—are available nowadays to facilitate the implementation of DL applications. Interestingly, software engineering (SE) researchers are also starting to explore the application of DL in traditional SE problems and areas, such as documentation \cite{8,9,10}, defect prediction \cite{11,12,13,14}, and testing \cite{15,16,17}.

However, since the cross-pollination between DL & SE is very recent, we do not have a clear map of the research conducted by combining these two areas. This map can help other researchers with interest on starting to work on the application of DL in SE. It can also help

\textsuperscript{1}https://www.tensorflow.org
\textsuperscript{2}https://pytorch.org
researchers that already work with DL & SE to have a clear picture of similar research in the area. Finally, mapping the research conducted in the intersection of DL & SE might help practitioners and industrial organizations to better understand the problems, solutions, and opportunities that exist in this area.

In this article, we provide the first results of our ongoing effort to review and summarize the most recent and relevant literature about DL & SE. To this purpose, we collect and analyze 81 papers recently published in major SE conferences and journals. We show the growth of the number of papers about DL & SE over the years. We also reveal the most common recent problems tackled by such papers. Finally, we provide data on the most common DL techniques used by SE researchers.

2 Deep Learning in a Nutshell

Deep Learning (DL) is a subfield of Machine Learning (ML) that relies on multiple layers of Neural Networks (NN) to model high level representations [18]. Similarly to traditional ML, DL techniques are suitable for classification, clustering, and regression problems. To better understand how DL differs from ML, suppose we are trying to classify which modules in a system are likely to be defective. If we decide to use conventional machine learning, we need a labeled dataset with relevant features able to distinguish defective from non-defective modules. To create this dataset, we usually apply several feature extraction approaches to extract meaningful features, and then train our model. In this point relies the key difference between traditional ML and DL techniques. While in traditional ML approaches the features are handcrafted, with DL they are selected by neural networks automatically [19, 20, 21].

Currently, there are many types of NNs, such as Convolutional Neural Networks, Recurrent Neural Networks, Auto-Encoders, Generative Adversarial Networks, and Deep Reinforcement Learning [18]. In the following, we outline four common classes of NNs that are useful in several SE problems:

**Multilayer Perceptrons (MLP):** They are suitable on classification and regression prediction problems. MLPs can be adapted to different types of data, such as image, text, and time series data. In addition, when evaluating the performance of different algorithms on a particular problem, we can use MLP results as baseline of comparison. Basically, MLPs consist of one or more layers of neurons. The input layer receives the data, the hidden layers provide abstraction levels, and the output layer is responsible to make predictions.
Convolutional Neural Networks (CNN): Although, they are designed for image recognition, we can use CNN for other classification and regression prediction problems. They also can be adapted to different types of data, such as image, text, and sequence input data. In summary, the input layer in a CNN receives the data and the hidden layers are responsible for feature extraction. There are three types of layers in a CNN, such as convolution layers, pooling layers, and fully-connected layers. The convolution layer performs a filter to an input multiple times to build a feature map and the pooling layer is responsible for reducing the spatial size of the feature map. Then, the CNN output can feed for instance a fully connected layer to create the model and make predictions.

Recurrent Neural Networks (RNN): They are a specialized type of NN for sequence prediction problems, i.e., they are designed to receive historical sequence data and predict the next output value(s) in the sequence. The main difference regarding the traditional MLP can be thought as loops on the MLP architecture. The hidden layers do not only use the current input, but also the previously received inputs. Conceptually, this feedback loop add memory to the network. The Long Short-Term Memory (LSTM) is a special type of RNN able to learn long-term dependencies. Specially, LSTM is one of the most used RNNs in many different applications with outstanding results [22, 23].

Hybrid Neural Network Architectures (HNN): They refer to architectures using two or more types of NNs. Usually, CNNs and RNNs are used as layers in a wider model. As an example from the industry, Google’s translate service uses LSTM RNN architectures [1].

3 Methodology

To collect the papers, we searched for deep learn* in the following digital libraries: Scopus, ACM Digital Library, IEEE Xplore, Web of Science, SpringerLink and Wiley Online Library. However, we only considered papers published in the software engineering conferences and journals indexed by CSIndexbr [24], which is a Computer Science Index system. CSIndexbr is considered a GOTO ranking [25], i.e., information systems that provide good, transparent, open, and objective data about CS departments and institutions [4].

The software engineering venues listed by CSIndexbr are presented in Table 1. As can be observed, the system indexes 15 conferences and 12 journals in software engineering, including

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3 https://csindexbr.org
4 http://gotorankings.org

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Table 1: Venues

| Acronym | Name |
|---------|------|
| ICSE    | Int. Conference on Software Engineering |
| FSE     | Foundations of Software Engineering |
| MSR     | Mining Software Repositories |
| ASE     | Automated Software Engineering |
| ISSTA   | Int. Symposium on Software Testing and Analysis |
| ICSME   | Int. Conference on Software Maintenance and Evolution |
| ICST    | Int. Conference on Software Testing, Validation and Verification |
| MODELS  | Int. Conference on Model Driven Engineering Languages and Systems |
| SANER   | Int. Conference on Software Analysis, Evolution and Reengineering |
| SLPC    | Systems and Software Product Line Conference |
| RE      | Int. Requirements Engineering Conference |
| FASE    | Fundamental Approaches to Software Engineering |
| ICPC    | Int. Conference on Program Comprehension |
| ESEM    | Int. Symposium on Empirical Software Engineering and Measurement |
| ICSA    | Int. Conference on Software Architecture |
| IEEE TSE | IEEE Transactions on Software Engineering |
| ACM TOSEM | ACM Transactions on Software Engineering and Methodology |
| JSS     | Journal of Systems and Software |
| IEEE Software | IEEE Software |
| EMSE    | Empirical Software Engineering |
| SoSyM   | Software and Systems Modeling |
| IST     | Information and Software Technology |
| SCP     | Science of Computer Programming |
| SPE     | Software Practice and Experience |
| SQJ     | Software Quality Journal |
| JSEP    | Journal of Software Evolution and Process |
| REJ     | Requirements Engineering Journal |

top-conferences (ICSE, FSE, and ASE), top-journals (IEEE TSE and ACM TOSEM) and also next-tier conferences (MSR, ICSME, ISSTA, etc) and journals (EMSE, JSS, IST, etc). CSIndexbr follows a quantitative criteria, based on metrics such as h5-index, number of papers submitted and accepted to index a conference or journal.

By searching for *deep learn* we found 141 papers in the conferences and journals listed in Table 1. The search was performed on September 15, 2019. Then, we removed papers with less than 10 pages, due to our decision to focus in full papers only. The only exception are papers published at IEEE Software (magazine). In this case, we defined a threshold of six pages to select the papers. By applying this size threshold, we eliminated 49 papers.
Then, we manually read the title and abstract of the remaining papers to confirm they indeed qualify as research that uses DL on SE-related problems. As a result, we eliminated 11 papers, including 5 papers that are not related to SE (e.g., one paper that evaluates an “achievement-driven methodology to give students more control of their learning with enough flexibility to engage them in deeper learning”), two papers published in other tracks (one paper at ICSE-SEET and one paper at ICSE-SEIP), two papers that only mention deep learning in the abstract, and two papers that were supersed by a journal version, i.e., we discarded the conference version and only considered the extended version of the work. Our final dataset has 81 papers.

4 Results

4.1 Publication Date

In our data collection, we did not define an initial publication date for the candidate papers. Despite that, we found a single paper published in 2015. All other papers are from subsequent years, as illustrated in Figure 1. Although the year is not finished, we have more papers published in 2019 than in 2018, which shows an increasing interest for applying deep learning in software engineering.

Figure 1: Papers by year
4.2 Authors Affiliation
We found 12 papers (14.8%) with at least one author associated to industry. Microsoft Research has the highest number of papers (3 papers), followed by Clova AI, Facebook, Grammatech, Nvidia, Accenture, Fiat Chrysler, IBM, and Codeplay (each one with a single paper).

4.3 Authors Country
Figure 2 shows a chart with the number of papers according to the authors country. Since papers can have authors from multiple countries, the sum is greater than 81 papers (the number of papers we reviewed in the study). Most papers have at least one Chinese author (33 papers), followed by USA (31 papers) and Australia (16 papers). We found authors from 20 countries.

4.4 Publication Venues
Figure 3 shows a chart with the number of papers by publication venue. In our dataset, 61 papers are from conferences (75.3%) and 20 papers from journals (24.7%). ICSE and FSE
concentrate most papers (24 papers or 29.6%). IEEE TSE is the journal with the highest number of papers (7 papers, 8.6%). We did not find papers about DL & SE in nine venues: MODELS, SLPC, RE, FASE, ICSA, ACM TOSEM, SoSyM, SCP and SQJ.

![Figure 3: Papers by venue](image)

### 4.5 Research Problem

Regarding the investigated research problem, we classified the papers in three principal groups: (1) papers that investigate the usage of SE tools and techniques in the development of DL-based systems; (2) papers that propose the usage of DL-based techniques to solve SE-related problems; and (3) position papers or tutorials. Figure 4 summarizes our classification. The following subsections describe the papers in each group.

#### 4.5.1 Using Software Engineering Techniques in Deep Learning-based Software

We classified 10 papers in this category (12.3%), including papers that adapt SE tools and techniques to DL-based software (8 papers) and papers that describe empirical studies of DL-based software (2 papers). Papers that apply SE to DL are mostly focused on solving particular problems that appear when testing DL-based software [26, 27, 28, 29, 30, 31]. However, we also found papers that describe quantitative metrics to assess DL-based software [32] and to support the deployment of DL-based software [33]. Finally, we found two
empirical studies of DL-based software, both investigating the characteristics of the bugs reported in such systems [34, 35].

4.5.2 Using Deep Learning Techniques in Software Engineering Problems

The usage of DL in SE is concentrated in three main problems: documentation, testing, and defect prediction. We provide more details in the following paragraphs:

**Documentation:** This category has the highest number of papers (13 papers, 16%). Seven papers study problems associated to StackOverflow questions and answers, including the usage of DL techniques to cluster related posts [9, 36, 37, 38], to recommend tags [8], cross-language posts search, i.e., translating non-English queries to English before searches [9], and to extract API tips [39]. Furthermore, we found papers about the automatic generation of code comments [40], the automatic identification of source code fragments in videos [10, 41], the classification of JavaDoc-based documents [42], and on source code summarization, i.e., using DL techniques to provide a high-level natural language description of the function performed by a code unit [43].
Testing: We found seven papers (8.6%) using DL in software testing, covering fuzzing tests [44, 45, 46], fault localization [47, 17], mutation testing [15], and testing of mobile apps [16].

Defect Prediction: We also found seven papers (8.6%) that use DL for defect prediction. Three papers use DL to extract semantic features directly from source code to improve defect prediction models [13, 12, 48]. Other papers also extract semantic features, but from commit descriptions [14] or commit sequences [49]. Finally, there are papers that investigate the usage of particular DL models, such as deep forests [50] and stacked denoising autoencoders [11].

Other research problems: Other important research problems handled using deep learning are code search [51, 52, 53, 54], security [55, 56, 57, 58], and software language modeling [59, 60, 61, 62]. The next most investigated research problems, with three papers each, are bug localization [63, 64, 65] and clone detection [66, 67, 68]. We also found two papers on each of the following problems: code smell detection [69, 70], mobile development [71, 72], program repair [73, 74], sentiment analysis [75, 76], and type inference [77, 78].

Finally, we found one paper about each of the following problems: anomaly detection [79], API migration [80], bug report summarization [81], decompilation [82], design patterns detection [83], duplicate bug detection [84], effort estimation [85], formal methods [86], program comprehension [87], software categorization [88], software maintenance [89], traceability [90], and UI design [91].

4.5.3 Position Papers

We classified three papers (3.7%) in this category, all published at IEEE Software. They describe the challenges and opportunities of using DL in automotive software [92, 93] or provide a quick tutorial on machine learning and DL [94].

4.6 Neural Networks Techniques

Figure 5 shows a chart with the most common deep learning techniques used by the analyzed papers. The most common technique is Convolutional Neural Network (CNN) (18 papers, 22.2%), followed by Recurrent Neural Networks (RNN) (17 papers, 20.9%) and Hybrid Neural Networks (HNN) (12 papers, 14.8%).

Table 2 shows the distribution of the DL techniques by research problem. As we can observe, RNNs are used in all problems, with the exception of security and bug localization.
Figure 5: Papers by deep learning technique

Table 2: Neural networks techniques by research problem

| Problem                        | CNN | RNN | HNN | LSTM | DBN | MLP |
|--------------------------------|-----|-----|-----|------|-----|-----|
| Documentation                  | ⬤   |     |     |      |     |     |
| Defect prediction              |     | ⬤   |     | ⬤    |     |     |
| Testing                        | ⬤   | ⬤   | ⬤   | ⬤    |     |     |
| Code search                    |     | ⬤   |     |      |     |     |
| Security                       | ⬤   |     |     |      |     |     |
| Software language modeling     |     |     | ⬤   |      |     |     |
| Bug localization               | ⬤   |     |     | ⬤    |     |     |
| Clone detection                |     | ⬤   |     | ⬤    |     |     |

Although CNN are used in more papers (18 papers), they have focus in only four problems (documentation, testing, bug localization, and clone detection).
5 Related Work

We found that Li, Jiang, Ren, Li, and Zhang also provide an arXiv preprint describing a literature review on the usage of DL in SE [95]. However, they review papers published before March, 2018, while we are covering papers published before September, 2019. This fact probably explains the difference regarding papers in top conferences: they report 14 papers at ICSE/FSE/ASE, whereas we are reporting 30 papers. Moreover, they only list papers from two journals (IST and Expert Systems and Applications), while we found papers in five journals and one magazine. Consequently, we analyze, for example, seven papers published at IEEE TSE. By contrast, they consider a broad range of conferences, e.g., SEKE, QRS, SNAPL. Finally, we provide an analysis of the neural networks used by the reviewed papers according to the research problem they investigate.

6 Conclusion

In this work, we analyzed 81 recent papers that apply DL techniques to SE problems or vice-versa. Our main findings are as follows:

- DL is gaining momentum among SE researchers. For example, 35 papers (43.2%) are from 2019 and only one paper from 2015.
- The authors of most papers are from China (33 papers) or USA (31 papers).
- 12 papers (14.8%) have at least one author from industry.
- The top-3 research problems tackled by the analyzed papers are documentation (13 papers), defect prediction (7 papers), and testing (7 papers).
- The most common neural network type used in the analyzed papers are Convolutional Neural Network (CNN) and Recurrent Neural Networks (RNN).

The list of papers and the data analyzed in this work are available at: https://docs.google.com/spreadsheets/d/1wRIqYVh-qXEocfoup8A60I0GaCmbcXHgnt_YZmD-e-Q/edit?usp=sharing

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