Interpreting Arabic Transformer Models

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Abstract

Arabic is a Semitic language which is widely spoken with many dialects. Given the success of pre-trained language models, many transformer models trained on Arabic and its dialects have surfaced. While these models have been compared with respect to downstream NLP tasks, no evaluation has been carried out to directly compare the internal representations. We probe how linguistic information is encoded in Arabic pre-trained models, trained on different varieties of Arabic language. We perform a layer and neuron analysis on the models using three intrinsic tasks: two morphological tagging tasks based on MSA (modern standard Arabic) and dialectal POS-tagging and a dialectal identification task. Our analysis enlightens interesting findings such as: i) word morphology is learned at the lower and middle layers ii) dialectal identification necessitate more knowledge and hence preserved even in the final layers, iii) despite a large overlap in their vocabulary, the MSA-based models fail to capture the nuances of Arabic dialects, iv) we found that neurons in embedding layers are polysemous in nature, while the neurons in middle layers are exclusive to specific properties.

1 Introduction

Arabic is a linguistically rich language, with its structures realized using both concatenative and templatic morphology. The agglutinating aspect of the language adds to the complexity where a given word could be formed using multiple morphemes. For example, the word فُسْقِّيْناكُمْ (faṣqīnākum) “we gave it to you to drink” combines a conjunction, a verb, and three pronouns. At another longitude, Arabic has three variants: Classical Arabic (CA), Modern Standard Arabic (MSA) and Dialectal Arabic (DA). While the MSA is traditionally considered as the de facto standard

in the written medium and DA being the predominantly spoken counterpart, this has changed recently (Mubarak and Darwish, 2014; Zaidan and Callison-Burch, 2014). Due to the recent influx of Social Media platforms, dialectal Arabic now has a significant presence in the written medium also.

Transfer learning from contextualized representations learned in pre-trained language models have revolutionized the arena of downstream NLP tasks. A plethora of transformer-based language models, trained in dozens of languages are uploaded every day now. Arabic is no different. Several researchers have released and benchmarked pre-trained Arabic transformer models such as AraBERT (Antoun et al., 2020), ArabicBERT (Safaya et al., 2020), CAMeLBERT (Inoue et al., 2021), MARBERT (Abdul-Mageed et al., 2020) and QARIB (Abdelali et al., 2021), etc. These models have demonstrated state-of-the-art performance on many tasks as well as their ability to learn salient features for Arabic. One of the main differences among these models is the genre and amount of Arabic data they are trained on. For example, AraBERT was trained only on MSA, ArabicBERT additionally used DA during training, and CAMeLBERT-mix used a combination of all types of Arabic text for training. Multilingual models such as mBERT are mostly trained on Wikipedia and CommonCrawl data which is predominantly MSA (Suwaileh et al., 2016). Figure 1 summarizes the training data regimes of these models.

This large variety of Arabic pre-trained models motivates us to question whether and how their representations encode various linguistic concepts and tasks. To this end, we present the first work on interpreting deep Arabic models. We experiment with nine transformer models including: five Arabic BERT models, Arabic ALBERT, Arabic Electra, and two multilingual models (mBERT and XLM). We analyze their representations with respect to three tasks: namely MSA and dialectal
parts-of-speech tagging and Dialect Identification. While the first task is MSA oriented, the other two involves DA. This allows us to compare the representations of Arabic transformer models using tasks involving different varieties of Arabic languages.

We analyze representations of the network at layer-level and at neuron-level using diagnostic classifier framework (Hupkes et al., 2018). The overall idea is to extract feature vectors from the learned representations and train probing classifiers towards understudied auxiliary tasks (of predicting morphology or identifying dialect). Our results show that:

**Network and Layer Analysis**
- Lower and middle layers learn the most about word morphology
- The knowledge required to solve the dialectal identification is preserved in the higher layers

**Neuron Analysis**
- The salient neurons with respect to a property are well distributed across the network
- First (embedding) and last layers of the models contribute a substantial amount of salient neurons for any downstream task
- The neurons of embedding layer and the last layer are polysemous in nature while the neurons of middle layers specializes in specific properties

**MSA vs. Dialect**
- Although dialects of Arabic are closely related to MSA, the pre-trained models trained using MSA only do not implicitly learn nuances of dialectal Arabic

## 2 Methodology

Our methodology is based on the class of interpretation methods called as the *Probing Classifiers*. The central idea is extract the activation vectors from a pre-trained language model as static features. These activation vectors are then trained towards the task of predicting a property of interest, a linguistic task that we would like to probe the representation against. The underlying assumption is that if the classifier can predict the property, the representations implicitly encode this information. We train layer- and neuron-wise probes using logistic-regression classifiers.

Formally, consider a pre-trained neural language model \( M \) with \( L \) layers: \( \{l_1, l_2, \ldots, l_L\} \). Given a dataset \( D = \{w_1, w_2, \ldots, w_N\} \) with a corresponding set of linguistic annotations \( T = \{t_{w_1}, t_{w_2}, \ldots, t_{w_N}\} \), we map each word \( w_i \) in the data \( D \) to a sequence of latent representations:

\[
D \xrightarrow{M} z = \{z_1, \ldots, z_N\}
\]

The layer-wise probing classifier is trained by minimizing the following loss function:

\[
L(\theta) = -\sum_i \log P_\theta(t_{w_i} | w_i)
\]

where

\[
P_\theta(t_{w_i} | w_i) = \frac{\exp(\theta \cdot z_i)}{\sum_{i'} \exp(\theta \cdot z_{i'})}
\]

is the probability that word \( i \) is assigned property \( t_{w_i} \).

For neuron analysis, we use *Linguistic Correlation Analysis* (LCA) as described in (Dalvi et al., 2019a). LCA is also based on the probing classifier paradigm. However, they used elastic-net regularization (Zou and Hastie, 2005) that enables the selection of both focused and distributed neurons. The loss function is as follows:

\[
L(\theta) = -\sum_i \log P_\theta(t_{w_i} | w_i) + \lambda_1 \|\theta\|_1 + \lambda_2 \|\theta\|_2^2
\]

The regularization parameters \( \lambda_1 \) and \( \lambda_2 \) are tuned using a grid-search algorithm. The classifier assigns weight to each feature (neuron) which serves as their importance with respect to a class like Noun. We ranked the neurons based on the absolute weights for every class. We select salient neurons for the task such as POS by iteratively selecting top neurons of every class.

A minimum set of neurons is identified by iteratively selecting top neurons that achieves classification performance comparable (within a certain threshold) to the *Oracle* – accuracy of the classifier trained using all the features in the network.
3 Experimental Setup

In this section, we describe our experimental setup including the Arabic transformer models, probing tasks that we used to carry the analysis, and the classifier settings.

3.1 Pre-trained Models

We select a number of Arabic transformer models, trained using various varieties of Arabic and based on different architectures. Table 1 provides a summary of these models. In the following, we describe each model and the dataset used for their training.

**AraBERT** was trained using a combination of 70 million sentences from Arabic Wikipedia Dumps, 1.5B words Arabic Corpus (El-khair, 2016) and the Open Source International Arabic News Corpus (OSIAN) from (Zeroual et al., 2019) 2019. The final corpus contained mostly MSA news from different Arab regions.

**ArabicBERT** Safaya et al. (2020) pretrained a BERT model using a concatenation of Arabic version of OSCAR (Ortiz Suárez et al., 2019), a filtered subset from Common Crawl and a dump of Arabic Wikipedia totalling to 8.2B words.

**CAMeLBERT** Inoue et al. (2021) combined a mixed collection of MSA, Dialectal and Classical Arabic texts with a total of 17.3B tokens. They used the data to pre-train CAMeLBERT-Mix model.

**MARBERT** Abdul-Mageed et al. (2020) combined a dataset of 1B tweets that covering mostly Arabic dialects and Arabic Gigaword 5th Edition, OSCAR (Ortiz Suárez et al., 2019), OSIAN (Zeroual et al., 2019) and Wikipedia dump totally up to 15.6B tokens.

**mBERT** was trained using a subset of OSCAR (Ortiz Suárez et al., 2019) and a dump of Wikipedia and selecting around 4.4 Billion words (Safaya, 2020). The model differs from traditional BERT architecture by introducing self-supervised loss and using repeating layers which results in a small memory footprint (Lan et al., 2020).

**AraELECTRA** Clark et al. (2020) introduced ELECTRA models that are trained to distinguish "real" input tokens vs "fake" input tokens generated by another neural network. The Arabic ELECTRA was trained on 77GB of data that combined OSCAR, Arabic Wikipedia dump, the 1.5B words Arabic Corpus, the OSIAN Corpus and Assafir news articles (Antoun et al., 2021). Different than other models, AraELECTRA uses a hidden layer size of 256 while all other models have 768 neurons per layer.

**Multilingual BERT** Google research released BERT multilingual base model pretrained on the concatenation of monolingual Wikipedia corpora from 104 languages with a shared word piece vocabulary of 110K.

**XLM** Conneau et al.(2020) is a multi-lingual version of RoBERTa, trained on 2.5TB Common-Crawl data. The model trained on 100 different languages.

3.2 Probing Tasks

We consider three probing tasks to analyze and compare the models:

**POS Tagging on Arabic Treebank (ATB):** The Arabic Treebank Part1 v2.0 and Part3 v1.0 with a total of 515k tokens labeled at the segment level with POS tags. The data is labeled with 42 distinct tags. The data is a combination of newswire text from An-Nahar and Agence France Presse corpus (Maamouri et al., 2004).

**POS Multidialects (DIA):** A total of 1.4k tweets from four Arabic dialects, namely Egyptian (EGY), Levantine (LEV), Gulf (GLF), and Maghrebi (MGR). The tweets were morphologi-
cally tagged (Samih et al., 2017) using a reduced subset of 22 tags.

**Dialect Identification (DID):** This task is related to codeswitching and language identification (LID) between MSA and Egyptian dialect on social media content. The data comprises of intrasentential code switched sentences used for the Second Shared Task on Language Identification in Code-Switched Data. The data contains over 11k sentences, labeled with 8 labels: lang1, lang2, fw, mixed, unk, ambiguous, other and named entities (ne) (Molina et al., 2016).

### 3.3 Post-hoc Classifier

We used the NeuroX toolkit (Dalvi et al., 2019b) to perform our analysis. Our probe is a linear classifier with categorical cross-entropy loss, optimized by Adam (Kingma and Ba, 2014). For neuron-analysis, the classifier additionally used the elastic-net regularization. The regularization weights are trained using grid-search algorithm. Training is run with shuffled mini-batches of size 512 and stopped after 10 epochs. Linear classifiers are a popular choice in analyzing deep NLP models due to their better interpretability (Qian et al., 2016). Hewitt and Liang (2019) have also shown linear probes to have higher Selectivity, a property deemed desirable for more interpretable probes. We perform control task experiments to validate the findings of our probing models. For sub-word based models, we use the average activation value to be the representative of the word. We additionally normalize the embeddings using znorm (Sajjad et al., 2021) as it has shown to provide better ranking of neurons with respect to a property.

### 4 Analysis and Discussion

Our goal is to carry out a comparative investigation of the knowledge encoded in different Arabic transformer models. First we compare the representations in terms of how much linguistic information is preserved in the network using the overall accuracy on the understudied auxiliary tasks. Then we analyze how such information is preserved across individual layers of the model. Lastly, we analyze the distribution of neurons across the model with respect to these tasks.

#### 4.1 Network Analysis

We train a post-hoc classifier towards each probing task using the entire network as features. Table 2 shows the performance of the classifier across probing tasks. The high accuracy reflects that a non-trivial knowledge of morphology and dialects is captured within the learned representations. The high selectivity numbers (See Sel. in Table 2) further support that the post-hoc classifier is not memorizing the probing tasks and the knowledge is captured within the underlying representations.

Comparing the models, we found CamelBERT to perform consistently well across all the tasks. In comparison, the models trained using MSA data only (for example mBERT) did poorly on the dialect related tasks, despite the significant overlap between MSA and dialectal vocabulary. This shows that to capture specific dialectal nuances these transformer models need to train/fine-tune on dialectal data.

#### 4.2 Layer-wise Analysis

We now analyze how the understudied linguistic knowledge is distributed across the layers. We train a classifier for each probing task using representations of individual layers as features. The performance of the classifier serves as a proxy to the amount of task knowledge learned in each layer representation. Figure 2 provides per-layer accuracy for each of the tasks.

We see that the lower layers learn relatively less information about ATB. The best results are obtained using the representations from the middle layers, in most of the models. On the DIA task, CAMelBERT and AlBERT showed similar patterns as that of ATB. However, the performance of mBERT dropped from the middle layers onward while rest of the models showed a relatively flat curve across layers. For the DID task, we see a large variation across models. However just like DIA, mBERT performed the worse while CAMelBERT outperformed all models for both dialectal tasks. This reinforces our findings from the network analysis that models require dialectal data to learn dialect-specific knowledge.

We see an interesting difference on the DID task, as opposed to the morphological tasks, where the performance using the embedding layer is substantially lower than the contextualized layers. This reflects the nature of the DID task that requires learning non-local dependencies and sentence level phenomenon to accurately predict the dialect. For example, a lexical form can belong to two differ-

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4 We limit the presentation to fewer models for clarity purposes.
### 4.3 Neurons Analysis

We now study how the information is spread across neurons instead of layer by carrying a fine-grained analysis. We discover neurons responsible for a particular linguistic property and analyze: i) how many neurons are sufficient to represent a particular property, ii) how these neurons are distributed across layers. We use LCA (Dalvi et al., 2019a) to obtain a ranked list of neurons with respect to the understudied property. We select a minimum set of top neurons from the ranked list that yield close to the Oracle performance within a loss of 1% accuracy. We found 5%, 10% and 7% neurons to be optimal for ATB, DIA and DID tasks respectively. We additionally calculate selectivity using the top neurons only and confirm that the salient neurons are indeed learning the property. Table 3 summarizes the results (See Table 4 in the Appendix A for a more detailed result). Our results show that a small subset of features can achieve close to oracle performance. Other researchers have also shown that network exhibits distributivity and redundancy (Dalvi et al., 2020). Such a finding entails interesting frontier in efficient feature-based transfer learning, which is considered as a viable alternative to the traditional fine-tuning based transfer learning (Peters et al., 2019).

#### 4.3.1 Neuron Distribution

We further analyzed the distribution of selected neurons across layers. See Figure 3 for results. On the ATB, the embedding layer and the last layer contribute the most number of neurons for all models except ALBERT. The distribution results of DIA are quite mixed and we did not observe a consistent pattern across models. DID showed similar trend as that of ATB where embedding layer and the last layer has significant contribution to the salient neurons. The dominance of embedding layer and the last layers in salient neurons reflect the use of both focused non-contextualized information and non-local syntactic information for the task of ATB and DID. Please recall our discussion from Section 4.2.

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**Table 2: Classifier performance on “Test” sets using entire network as features**

| Models   | ATB     | DIA     | DID     |
|----------|---------|---------|---------|
| AraBERT  | 0.938   | 0.409   | 0.755   |
| ArabicBERT | 0.954   | 0.482   | 0.605   |
| CAMelBERT | 0.956   | 0.469   | 0.833   |
| MARBERT  | 0.952   | 0.481   | 0.819   |
| QARBERT  | 0.954   | 0.488   | 0.823   |
| mBERT    | 0.951   | 0.514   | 0.783   |
| AraELECTRA | 0.952   | 0.451   | 0.738   |
| ALBERT   | 0.945   | 0.437   | 0.771   |
| XLM      | 0.951   | 0.437   | 0.771   |

**Table 3: Classifier performance on “Test” sets using top neurons as features**

| Models   | ATB     | DIA     | DID     |
|----------|---------|---------|---------|
| AraBERT  | 0.934   | 0.488   | 0.793   |
| ArabicBERT | 0.940   | 0.508   | 0.833   |
| CAMelBERT | 0.949   | 0.511   | 0.851   |
| MARBERT  | 0.945   | 0.516   | 0.842   |
| QARBERT  | 0.950   | 0.527   | 0.836   |
| mBERT    | 0.952   | 0.506   | 0.797   |
| AraELECTRA | 0.952   | 0.506   | 0.797   |
| ALBERT   | 0.947   | 0.518   | 0.790   |
| XLM      | 0.953   | 0.518   | 0.790   |

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| ALBERT   | 0.947   | 0.518   | 0.790   |
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**Figure 2: Layer-wise accuracy for different tasks.**

(a) ATB  
(b) DIA  
(c) DID

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ent dialects depending on the context and requires syntactic information to disambiguate the dialect of the word. For example, “HAjp” (thing or need) is MSA in the context: 

\[ \text{Hafy HAjp IOn} \] (I am not in need to) or Egyptian: 

\[ \text{mfyc HAjp OSEb mn} \] (there is no thing difficult than). The contextual knowledge is essential to disambiguate in such cases.

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Comparing models, ALBERT is a clear outlier; the embedding layer has close to zero contribution in the top selected neurons and relatively higher number of neurons from the initial contextualized layers. Does it mean that the embedding layer is relatively weaker in the ALBERT architecture? Answer to this question requires explicit evaluation of word embedding using lexical tasks such as word similarity and word relatedness. However, this is out of the scope of this work.

4.4 Property-wise Analysis

The understudied linguistic tasks are composed of different properties such as Noun, Verb, Adjective. These properties differ in their linguistic roles. We further study the selected number of neurons across different properties, to see how specific linguistic properties are encoded in the network. Figure 4a shows distribution of neurons across ATB properties. We noticed that some properties are localized to fewer neurons (e.g. Interjection (UH), Personal pronoun (PRP), Wh-adverb (WRB)) where as some properties are distributed and require more neurons (e.g Adjective (JJ), Proper noun (NNP), Verb, past tense (VBD)). This observation is consistent across models. Similar observation can be seen in DIA (Figure 4b), where closed classes (e.g. Conjunction (CONJ), Preposition (PREP)) required less neurons while Nouns (NOUN) and Adjectives (ADJ) required relatively more neurons. This is not as apparent as the former ATB dataset due to the training data size. For DID (Figure 4c), the class “mixed” uses the least number of neurons as its occurrence in the corpus is far less than other tags.

Comparing models, AraELECTRA requires the highest number of neurons for most of the properties. We suspect that this is due to the small size of the hidden layers (AraELECTRA 256 vs. 768 other models) where the information is spread across multiple layers and in more neurons. Other notable observations are of mBERT and ALBERT for PUNC, where they require substantially less neurons than other models.

We further questioned how individual properties are encoded across layers in the network. Do they have similar neuron distribution pattern or there are specific properties which are learned more on higher layers than lower layers and vice versa. Figure 5 shows the distribution of selected neurons of CAMELBERT, AraBERT and ALBERT for a few open class and closed class properties. We did not observe a very consistent pattern with respect to open class and closed class properties. The property Noun (NN) is a clear outlier in the case of CAMELBERT and AraBERT, highest top neurons from the embedding layer and relatively less neurons from the last layers. On the contrary, VBD is also an open class category but its top neurons are dominated by the last layers. This is due to the fact that verbs in Arabic are highly inflected and syntactically complex. They typically combine multiple morphemes as seen in the former example of the verb in word “fOsqynAkmvh” that is composed of a conjunction, a verb, and three pronouns to form a single word. The verb representation is hence impacted by the surrounding affixes.

ALBERT has the most consistent per property pattern which is also aligned with overall ATB pattern (see Figure 3) i.e. Layer 2 and Layer 12 dominates in salient neurons for all properties. The relatively large number of neurons for NN are due to the open class nature of the property.

4.5 Polysemous Properties and Neurons

Further, we analyzed how top neurons of a property overlap with the top neurons of other proper-
ties. This may reflect the amount of polysemous neurons present in the network or the polysemous nature of linguistic properties. The latter is particularly possible in the case of Arabic which is agglutinative in nature. It is common for affixes such as preposition, determiner, pronouns to join with nouns, and adjectives to form composite constructions. Figure 6 shows the overlap of neurons across properties for pairs of consecutive layers for CAMeLBERT. The zeros in the diagonal means that none of the top neurons of a property are selected from that layer.

Looking at the overall intersection trend, the bulk of overlapping neurons are from the lower layers and the last layers. At the middle layers, less polysemous neurons are observed which means that the neurons learn specialized knowledge in the middle layers. We hypothesize that the increase in the polysemous neurons in the last layers is due to the objective function which may encourage less specialized neurons and require more distributed information. Comparing properties, we observed that Determiner (DT), Adjective (JJ) and Noun (NN) share top neurons. The ratio of such intersection can reach over 47% as in the case of Determiner “DT” and Noun “NN”. The word collocations in Arabic caused the sharing in these cases. Verb (VB) and DT present another interesting case where there is a large overlap for the non-contextualized layer (Layer 0) and with the presence of context, the network learns specialize neurons for each property and the percentage of polysemous neurons drop substantially till the last few top layers. As mentioned earlier, the increase of polysemous neurons for the higher layers is likely to be caused by the objective function.

5 Related Work

Work done on interpreting deep NLP models can be broadly classified into Concept Analysis and
Attribution Analysis. The former thrives on post-hoc decomposability, where we analyze representations to uncover linguistic (and non-linguistic) phenomenon that are captured as the network is trained towards any NLP task (Adi et al., 2016; Belinkov et al., 2017; Conneau et al., 2018; Liu et al., 2019; Tenney et al., 2019) and the latter characterize the role of model components and input features towards a specific prediction (Linzen et al., 2016; Gulordava et al., 2018; Marvin and Linzen, 2018). Our work falls into the former category. We carry out a layer and neuron-wise analysis on the Arabic transformer models. We used Diagnostic classifiers (Hupkes et al., 2018) to train layer and neuron-wise probes towards predicting linguistic properties of interest. To the best of our knowledge this is the first work on analyzing Arabic transformer models.

Suau et al. (2020) used max-pooling to identify relevant neurons (aka Expert units) in pre-trained models, with respect to a specific concept (for example word-sense). Mu and Andreas (2020) proposed a Masked-based Corpus Selection method to determine important neurons with respect to a concept. In this work, we used the Linguistic Correlation Analysis of Dalvi et al. (2019a) to perform neuron analysis.

6 Conclusion and Future Work

In this paper we carry out a post-hoc comparative analysis on a number of Arabic transformer models using 3 linguistic tasks. Our results enlighten interesting insights: i) neural networks learn non-trivial amount of linguistic knowledge with lower and middle layers capturing word morphology and higher layers learning more universal phenomenon, ii) we found that salient neurons are distributed across the network, but some layers contribute more salient neurons towards a task, iii) we found some neurons to be polysemous in nature while other capturing very specialized properties, iv) lastly we showed that MSA-based transformer models do not capture dialectal nuances despite have a large overlap with dialects. For future work, we aim to expand this analysis to include more tasks and other languages with a focus on analysing groups of related languages in the families of Semitic, Germanic or Latin languages.
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Appendix

Table 4 shows the performance loss for different thresholds. Highlighted thresholds were selected based on the 1% average performance loss. For the case of DIA, some overfitting is noticeable. Such case is reported in literature where the classifiers with large contextualized vectors tend to overfit when supervised data is insufficient (Hameed, 2018).
| Task | Threshold | AraBERT | AraBERT | CAMelBERT | MARBERT | QARiB | mBERT | AraELECTRA | ALBERT | XLM |
|------|-----------|---------|---------|-----------|---------|-------|-------|------------|--------|-----|
|      | 3.00%     | 0.914   | 0.915   | 0.929     | 0.916   | 0.924 | 0.924 | 0.868      | 0.935  | 0.938|
|      | 5.00%     | 0.934   | 0.940   | 0.949     | 0.945   | 0.950 | 0.941 | 0.912      | 0.947  | 0.953|
| ATB  | 7.00%     | 0.939   | 0.949   | 0.957     | 0.952   | 0.957 | 0.945 | 0.934      | 0.953  | 0.957|
|      | 10.00%    | 0.943   | 0.953   | 0.960     | 0.957   | 0.961 | 0.947 | 0.945      | 0.954  | 0.960|
|      | 20.00%    | 0.945   | 0.956   | 0.960     | 0.958   | 0.962 | 0.948 | 0.954      | 0.953  | 0.961|
|      | 50.00%    | 0.940   | 0.953   | 0.955     | 0.954   | 0.958 | 0.941 | 0.957      | 0.948  | 0.955|
|      | 100.00%   | 0.937   | 0.954   | 0.957     | 0.955   | 0.955 | 0.938 | 0.954      | 0.947  | 0.953|
|      | 3.00%     | 0.753   | 0.780   | 0.798     | 0.766   | 0.783 | 0.732 | 0.683      | 0.779  | 0.753|
|      | 5.00%     | 0.774   | 0.812   | 0.835     | 0.809   | 0.820 | 0.748 | 0.747      | 0.808  | 0.767|
| DIA  | 7.00%     | 0.788   | 0.831   | 0.847     | 0.830   | 0.834 | 0.757 | 0.776      | 0.815  | 0.783|
|      | 10.00%    | 0.793   | 0.833   | 0.851     | 0.842   | 0.836 | 0.775 | 0.794      | 0.818  | 0.790|
|      | 20.00%    | 0.794   | 0.840   | 0.857     | 0.850   | 0.851 | 0.768 | 0.809      | 0.814  | 0.806|
|      | 50.00%    | 0.784   | 0.832   | 0.840     | 0.844   | 0.847 | 0.752 | 0.814      | 0.798  | 0.799|
|      | 100.00%   | 0.770   | 0.818   | 0.831     | 0.826   | 0.829 | 0.734 | 0.803      | 0.790  | 0.776|
|      | 3.00%     | 0.829   | 0.876   | 0.879     | 0.879   | 0.885 | 0.809 | 0.840      | 0.864  | 0.833|
|      | 5.00%     | 0.854   | 0.892   | 0.897     | 0.907   | 0.908 | 0.821 | 0.868      | 0.881  | 0.860|
| DID  | 7.00%     | 0.860   | 0.901   | 0.910     | 0.916   | 0.917 | 0.832 | 0.882      | 0.885  | 0.865|
|      | 10.00%    | 0.872   | 0.905   | 0.914     | 0.918   | 0.920 | 0.837 | 0.887      | 0.892  | 0.878|
|      | 20.00%    | 0.880   | 0.908   | 0.917     | 0.922   | 0.923 | 0.846 | 0.890      | 0.893  | 0.878|
|      | 50.00%    | 0.876   | 0.902   | 0.909     | 0.915   | 0.915 | 0.840 | 0.896      | 0.888  | 0.871|
|      | 100.00%   | 0.864   | 0.892   | 0.896     | 0.903   | 0.903 | 0.823 | 0.906      | 0.877  | 0.858|

Table 4: Performance per models using different threshold $\delta$