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Handwritten Character Recognition Models Based on Convolutional Neural Networks

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Abstract: *This paper explores the possibility of using various convolutional neural network models to recognize handwritten Arabic characters. It discusses which of the existing convolutional neural network models best suits this task. The results are analyzed based on which conclusions are drawn regarding the effectiveness or ineffectiveness of specific convolutional neural network models. The paper provides an analysis of the efficiency of convolutional neural network models for the task of recognizing handwritten Arabic characters.*

Keywords—Arabic symbol recognition; artificial intelligence; computer vision; convolutional neural networks (CNN); machine learning; neural networks; symbol recognition

1. INTRODUCTION

On Earth, there are over seven thousand languages. Each ethnic group speaks its language, and each language belongs to a language family, with a total of approximately 250 unique language families. Each language represents the heritage of a specific nation, serving not only as a powerful means of communication and a tool for thought (thinking) but also as the spirit of the people, and their history [1].

The most common language today is Arabic, which is gaining more and more popularity every year. It is spoken by approximately 350 million people in 23 countries worldwide, where it is considered an official language. Arabic language is spoken by most of the countries of the Middle East and North Africa [2]. The task of recognizing handwritten Arabic characters is currently of great importance. Archaeology, paleontology, and linguistics are developing at an incredibly rapid pace, and the tasks they set for themselves often require automation. Given the prevalence of the Arabic language, scientists from different corners of the Earth have been studying methods to automate the process of Arabic character recognition. Ancient manuscripts, processing of banking data, and graphology tasks – are just a few examples of tasks that require constant improvement in the automation of character recognition processes [3].

Convolutional neural networks have proven to be the most effective in processing characters. The first convolutional neural network, LeNet, was developed specifically for solving the task of recognizing handwritten digits on digitized images of size 32×32 pixels [4]. From 1989 to the present day, convolutional neural networks have come a long way in their development and are now used in cryptography, medicine, linguistics, mathematics, philology, and more. New neural network models continue to be developed and improved constantly.

In this work, we will conduct a study on the effectiveness of existing convolutional neural network models for the task of processing handwritten Arabic characters.

The purpose of the work is to research of efficiency of different convolutional neural network models in the task of recognizing handwritten Arabic characters.

The object of research is the recognition of handwritten Arabic symbol recognition with convolutional neural networks.

2. RELATED WORKS

In the context of studying the methods for recognition of Arabic handwritten symbols that needed to know some linguistic aspects, several research works address the fundamental aspects of Arabic linguistics and its historical development was learned.

The works [1, 2] provides an introduction to the field of linguistics with a focus on philological specialties. The work highlights an introduction to the Arabic language and delves into fundamental linguistic concepts crucial for understanding and analyzing the Arabic language. Also, the history of the Arabic language, its features, and prospects for development are explored. The evolution of Arabic linguistics is discussed, along with the contribution of the Arabic language to the cultural and societal development of the region.

The papers [3-5] describe the features of the application of convolutional neural networks to the problem of recognizing Arabic characters. The authors of these works focused on the development of deep architectures capable of automatically extracting features from characters, which makes it possible to effectively determine the differences and features of handwritten Arabic characters. These works emphasize the importance of using convolutional neural networks to achieve high performance in Arabic symbol recognition tasks.

The papers [6-12] are dedicated to convolutional neural networks and their application in various tasks. They describe

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the structure and operation of convolutional neural networks, including their main layers and architectures, as well as explain how they can be used in different situations.

On the whole, the review of the literature concerning the recognition of handwritten Arabic characters reveals a vibrant and promising research domain that holds the potential to enhance the accuracy of character decipherment and contribute to more effective communication.

3. Materials and Models

Step 1: Finding and Collecting Data from which CNN Can Learn

The dataset called the Arabic Handwritten Characters Dataset has 16,800 elements [5]. The database contains training and a test set [5]. It should be noted that the training set has 13440 elements (480 images per cluster). As for the test set, it has 3360 elements (up to 120 images per cluster).

The examples of symbols from the dataset are shown in Fig. 1 [5].

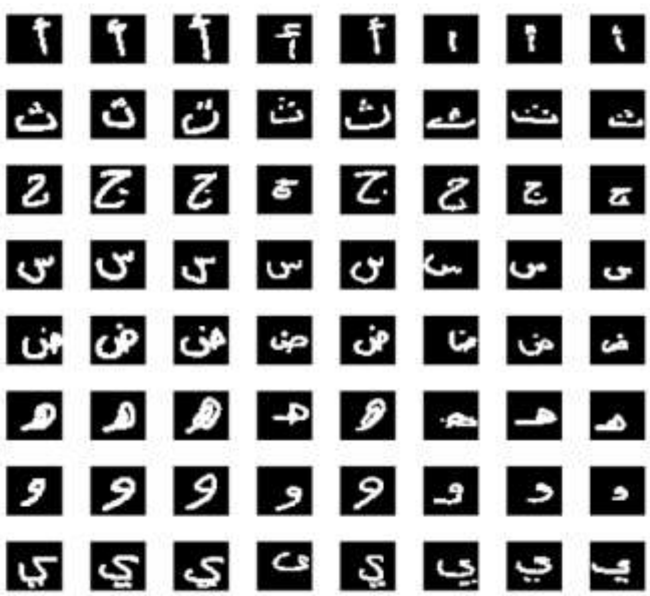

Fig. 1. *Example of symbols from dataset [5]*

Step 2: Checking for Possible Problems in the Arabic Character Recognition Task

The task of recognizing Arabic characters is not trivial, primarily because distinguishing Arabic symbols without the aid of a neural network is quite challenging for individuals who are not native speakers of the language. This difficulty arises due to certain characteristics of Arabic characters, which significantly differ from the familiar Latin and Cyrillic scripts for Western individuals. One prominent feature of writing Arabic characters is that they are written in a cursive style. Some characters have various writing forms, potentially complicating the training process for a neural network by increasing variations in character shapes [7].

Moreover, in different parts of a word or sentence, Arabic characters may have different writing forms, further complicating the recognition process [7]. The presence of dots in Arabic characters poses a significant challenge in recognizing them [7]. For example, by considering the characters ت [ta] and ث [sa], which represent entirely different sounds and have distinct pronunciations. The only difference in their written forms is that the character ث has an additional dot above ت.

This can complicate the processing and recognition of characters, leading the neural network to produce incorrect results when distinguishing between these two symbols. This is just one example, but each Arabic character has variations in writing, which presents a challenge for neural networks recognizing handwritten Arabic characters (Fig. 2 [1]).

alif	ا	za	ز	qaf	ق
ba	ب	sin	س	kaf	ك
ta	ت	shin	ش	lam	ل
tha	ث	sad	ص	mim	م
jim	ج	dad	ض	nun	ن
ha	ح	ta	ط	ha	ه
kha	خ	dha	ظ	waw	و
dal	د	ain	ع	ya	ي
dhal	ذ	ghain	غ		
ra	ر	fa	ف		

Fig. 2. *Arabic alphabet characters [1]*

Step 3: Describing Existing CNN Models for Recognition in Research

LeNet. There are a lot of efficient CNN models developed from the 90s of the 20th century. The First CNN model was developed and proposed in 1989 by Yann Lecun. LeNet [6] was created for the recognition of simple digit images. This neural network has seven layers as well as an input layer. All levels have parameters in the form of weights; it is these components that are subject to training. An image with a size of 32×32 pixels is submitted to the input. This size is enough to process any element from the database [6].

LeNet is an improvement of artificial intelligence in the framework of deep learning, which led to the significant development of Convolutional Neural Networks (CNNs). Following Yann LeCun’s example, many other researchers started developing and adapting their convolutional neural networks for various tasks. These adaptations led to significant progress in the field of computer vision and beyond.

AlexNet. AlexNet is a CNN that was developed to solve image classification problems; its efficiency is 84.7%, significantly outperforming previous methods [8].

This network has eight full layers, which, in turn, contain weights. It should be noted that five layers are convolutional, and the other three are fully connected [8].

VGG19. The VGG network [10, 11] showed that it is the depth of the network that is a particularly important component when solving recognition problems in CNNs. VGG19 contains 3×3 filters, and the number of filters in the structure is doubled each time, subject to a max pooling operation.

ResNet. ResNet, short for Residual Neural Network, is a revolutionary deep learning architecture that has greatly influenced the field of computer vision and deep learning. It was introduced in 2015 by Kaiming He et al. as a solution to learning problems for very deep neural networks [9].

It should be noted that there is a vanishing gradient problem when building deep networks. In the case when the depth of the network increases, the gradients acquire very small values, which, in turn, are obstacles to the qualitative study of significant data. This phenomenon complicates the training process and can lead to suboptimal results [9].

To solve this problem, ResNet introduced the concept of residual learning. Instead of trying to learn the desired underlying mapping, the network learns the residual mapping. Essentially, it aims to model the difference between a layer's inputs and outputs rather than learning the entire mapping from scratch. Residual blocks are at the heart of the ResNet architecture. Each residual block consists of a series of convolutional layers [9, 11]. The output of these layers is then added to the original input using skipping. By propagating the original input across the network, in addition to training residuals, gradients are more easily preserved during backpropagation, which alleviates the vanishing gradient problem. The identification label used in ResNet is an important element in maintaining depth and improving overall network performance. When the input and output dimensions of the residual block match, the fast connection directly adds the input to the output. If the dimensions differ, a 1×1 convolution layer is used to match the dimensions before adding. The success of ResNet has led to its widespread adoption and adaptation in numerous computer vision applications ranging from image classification, object detection, and segmentation to various other tasks. Moreover, ResNet’s fundamental idea of residual learning inspired the development of many subsequent architectures aimed at solving the learning problems of deep neural networks.

In summary, ResNet’s innovative approach to residual learning and the inclusion of skip connections has revolutionized deep learning, allowing extremely deep networks to be trained with superior performance on a wide range of computer vision tasks. Its influence continues to resonate in the field of artificial intelligence, leading to advances and breakthroughs in various fields.

GoogLeNet. The structure of GoogLeNet has significant differences from the structures of the previously mentioned networks, which are extremely effective today.

The structure of GoogLeNet provides:

1. 1×1 convolution to reduce the number of parameters.

2. Global Average Pooling leads to an increase in the cost of all calculations. In the GoogLeNet network, the 7×7 feature map is averaged to 1×1 [12].

3. For each layer, there is a fixed convolution size, which leads to much better processing of the studied objects at different scales [12].

4. An auxiliary classifier for training provides for the presence of branches of the classifier that are used exclusively during training. Thanks to these components, the problem of the disappearance of the gradient is solved.

Step 4: Preparing CNN Models for Testing

To prepare five convolutional neural networks for recognizing Arabic characters, a dataset of Arabic characters was collected and prepared for training and testing the models. The data was loaded and split into training and testing sets. Then, five convolutional neural networks were created, each with a softmax activation layer for character classification. Each model was trained on the training dataset using an optimizer and loss function. The performance of each model was evaluated on the test set using metrics such as accuracy and confusion matrix. Subsequently, the best-performing model was selected based on its performance. The selected models were tested on real-world data, and if necessary, hyperparameters were tuned or optimization techniques such as data augmentation or weight pruning were applied. Training, evaluation, and testing were repeated several times to achieve satisfactory results on new data. It is important to note that successful training and recognition of Arabic characters might have required multiple iterations and parameter tuning to achieve the best performance. Excluding differences in architectures, the training process of all neural network models follows the same algorithm. The flowchart of this algorithm is depicted in Fig. 3.

Step 5: Testing LeNet

For testing the application for recognizing emotions in marketing research on the effectiveness of advertising we use the Arabic Handwritten Characters Dataset dataset for handwritten Arabic symbol recognition. Application may be run by the client and follow up every little bug or mistake, especially in CNN accuracy in the recognition process.

The first tested model was the LeNet convolutional neural network (the results of testing in Fig. 4 and Fig. 5). In Fig. 4 and Fig. 5 we see the result of the Arabic symbols recognition process. As the training progresses, the accuracy steadily increases, and the loss decreases, indicating that the network is learning to recognize the handwritten Arabic characters better.

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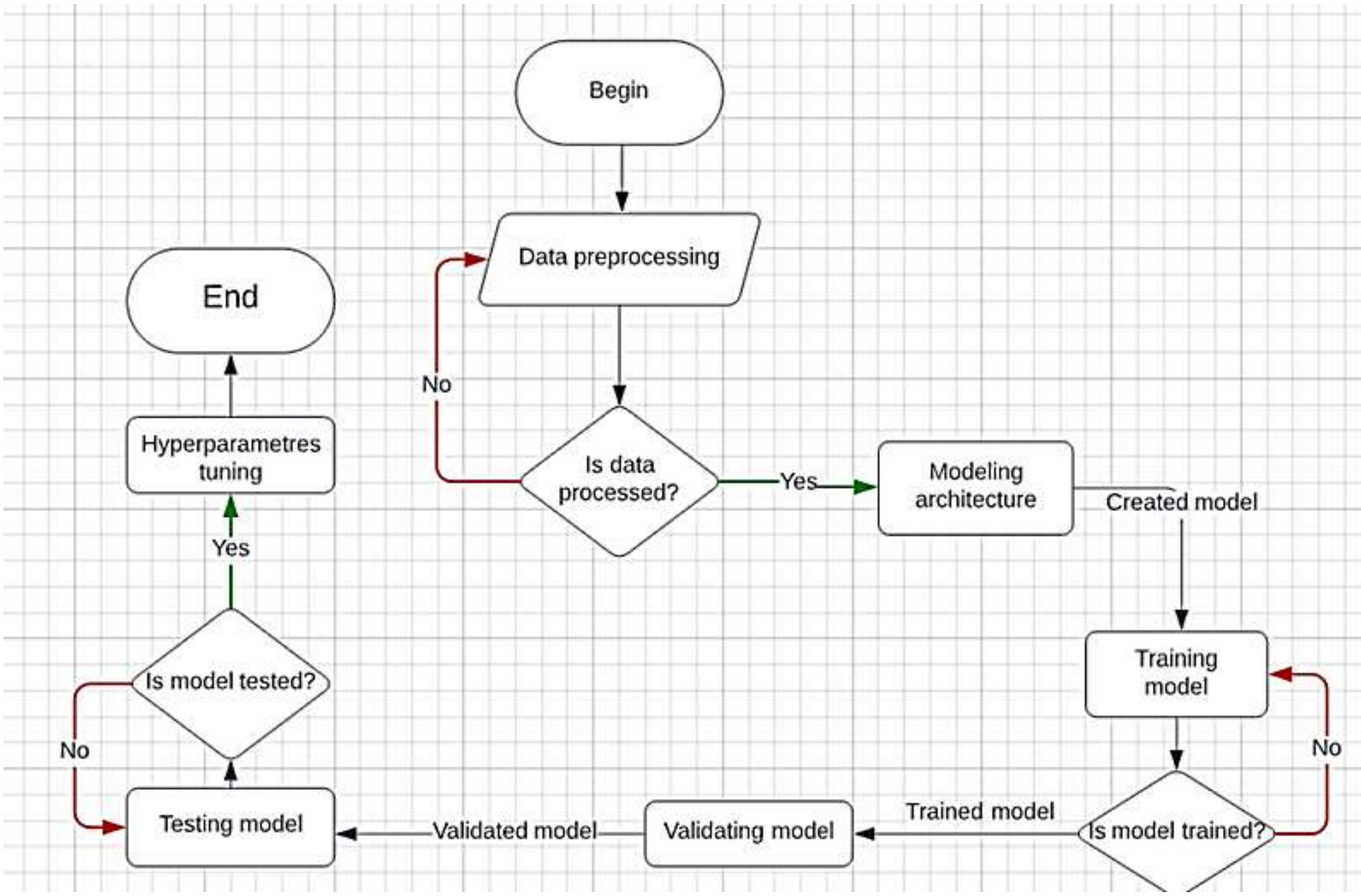

Fig. 3. *Block diagram of the learning process of the neural network*

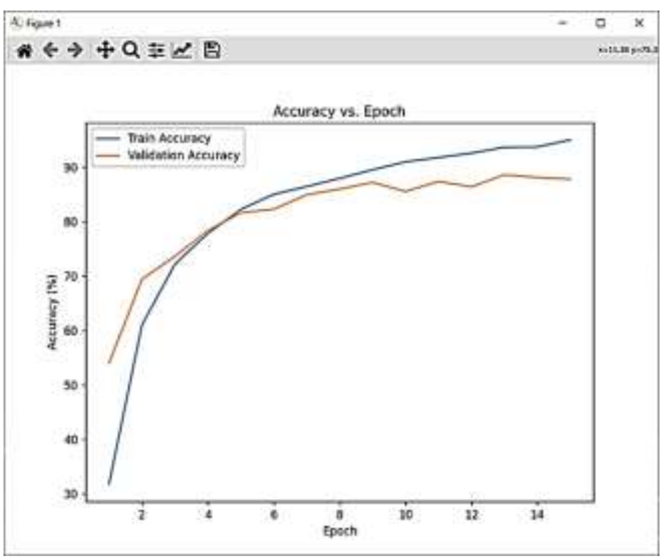

Fig. 4. *Result of recognizing Arabic handwritten characters with the convolutional neural network LeNet*

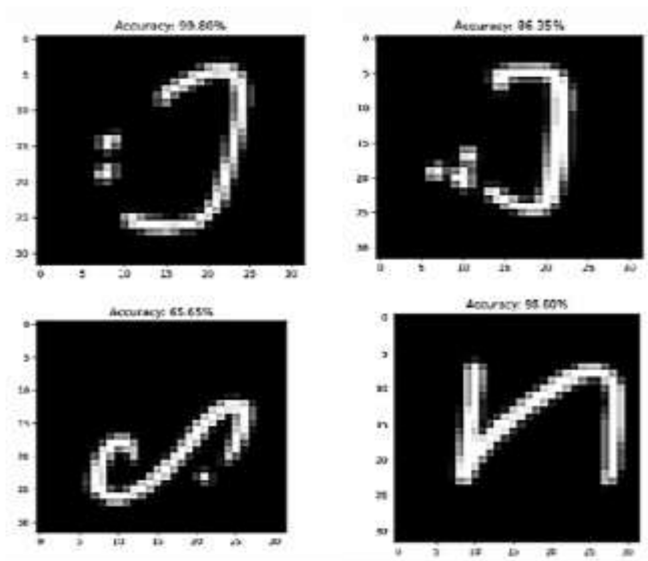

Fig. 5. *The example of recognizing handwritten Arabic characters with LeNet*

Also in Fig. 5, we see examples of Arabic symbols from the dataset and they're recognition accuracy with LeNet CNN.

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By the end of the 15 epochs, the training accuracy reaches around 94%, and the validation accuracy is around 87%. However, it's essential to note that test accuracy is the most critical metric as it shows how well the network generalizes to new, unseen data. In this case, the test accuracy is approximately 88%, which means the network is capable of recognizing handwritten Arabic characters with a high level of accuracy.

The next model for training is AlexNet (its results of testing in Fig. 6 and Fig. 7).

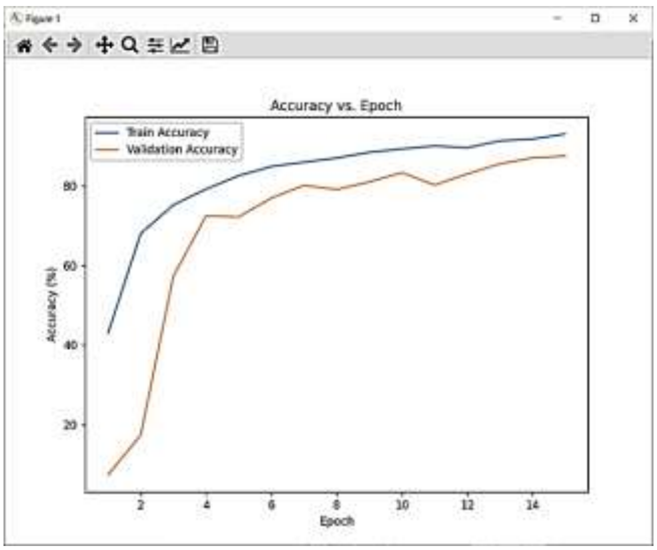

Fig. 6. *Result of recognizing Arabic handwritten characters with the convolutional neural network AlexNet*

Analyzing the training result, overall, these results can be considered good, especially if the context and task align with expectations.

Accuracy on training data: at the end of training, the model achieved an accuracy of approximately 92.56% on the training data. High accuracy on training data indicates that the model performed well on the provided data and predicts labels effectively within the training set.

At the end of the training, the model achieved an accuracy of approximately 85.12% on the validation data. This is also a good indicator, as validation accuracy helps assess how well the model generalizes its knowledge to new data it has not seen before. An accuracy of around 85% indicates a good ability of the model to generalize to new data.

The model achieved an accuracy of approximately 85.12% on the test data. Test data is used to evaluate the performance of the network by applying new data that was not known when the model was trained.

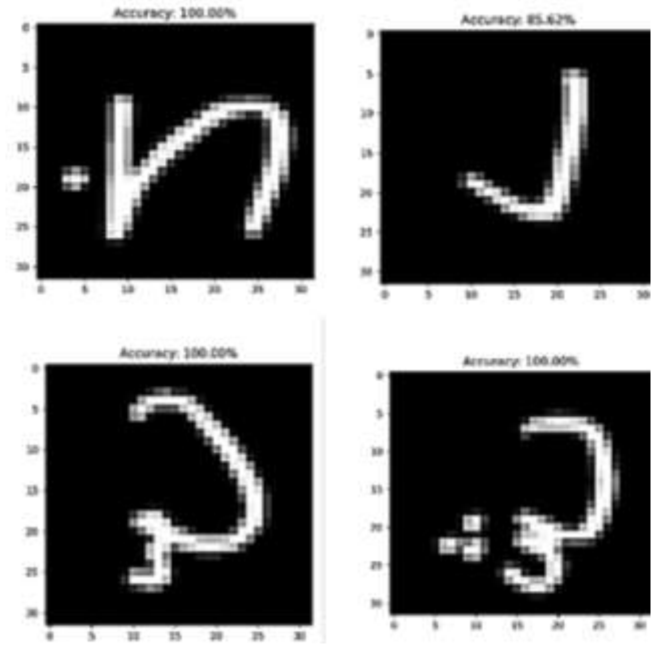

Fig. 7. *The example of recognizing handwritten Arabic characters with AlexNet*

An accuracy of around 85% on the test data indicates a good ability of the model to generalize to data that it has not been exposed to during training.

The results of testing VGG19 are shown in Fig. 8 and Fig. 9. Based on the results provided, the results of neural network training can be assessed as good. The accuracy of the test data set is about 94.55%, which indicates that the network has successfully trained and can accurately classify new data.

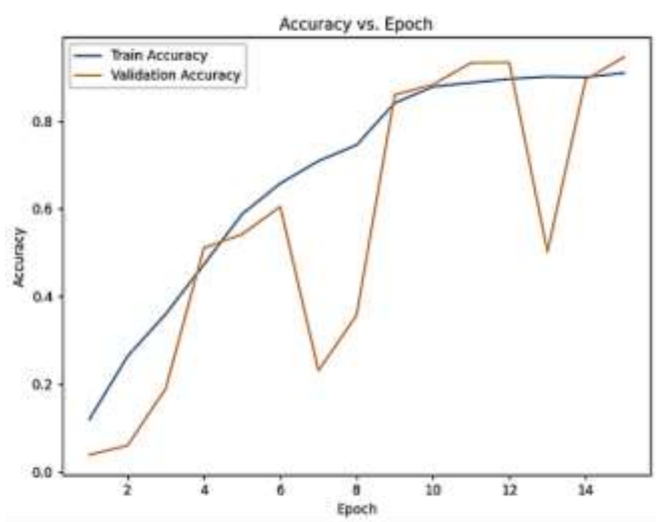

Fig. 8. *Result of recognizing Arabic handwritten characters with the convolutional neural network VGG19*

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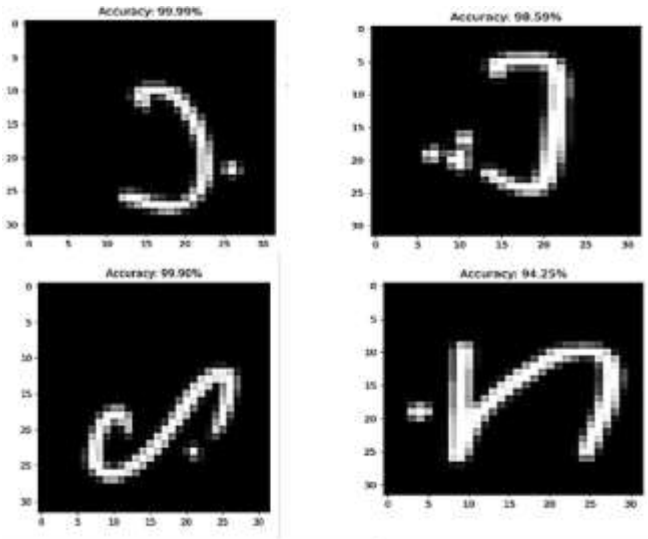

Fig. 9. *The example of recognizing handwritten Arabic characters with VGG19*

The dynamics of accuracy improvement and loss reduction over epochs also confirm the successful training of the model.

The main idea behind ResNet is to skip connections or shortcuts, which allows the network to learn residual functions instead of directly trying to learn the desired underlying mapping. These residual blocks help in mitigating the degradation problem, where adding more layers to a network leads to a decrease in performance due to vanishing gradients. Results of recognition are shown in Fig. 10 and Fig. 11.

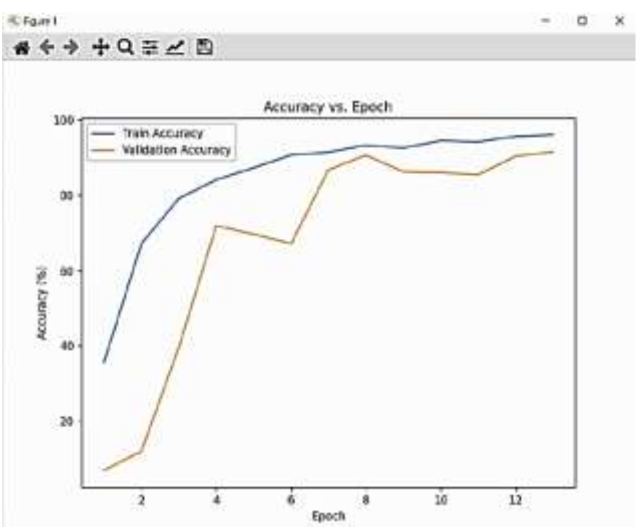

Fig. 10. *Result of recognizing Arabic handwritten characters with the convolutional neural network ResNet*

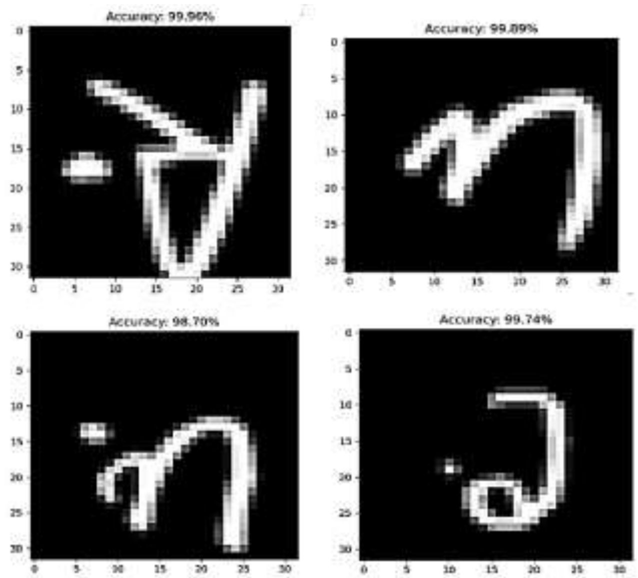

Fig. 11. *The example of recognizing handwritten Arabic characters with ResNet*

The overall analysis of the CNN performance reveals the following:

1. The accuracy on the test dataset is approximately 92.62%, which is a fairly high value and indicates a high likelihood of correctly classifying images.

2. The loss on the test dataset is approximately 0.2597, which is also a low value. Small loss values suggest that the model is fitting the data well and is capable of making accurate predictions.

Both accuracy and loss improve at each stage of development, both on the training and validation sets. This indicates that the model is successfully learning from the data and finding better parameters for more precise predictions.

The CNN model performs well in this image classification task.

The next model for training is GoogLeNet, and its results of testing are shown in Fig. 12 and Fig. 13.

The training results are considered as good. In the initial epochs, the accuracy and loss are typically low, as the network has not yet learned the data's features.

Over time, the accuracy increases and the losses decrease, indicating that the network starts to identify the data's characteristics and learn.

The accuracy of the test data also increases, reaching around 93.33%, which is quite a good result. The accuracy graph shows a consistent improvement throughout training, indicating good convergence of the network. The loss graph also decreases, further confirming that the network is learning successfully.

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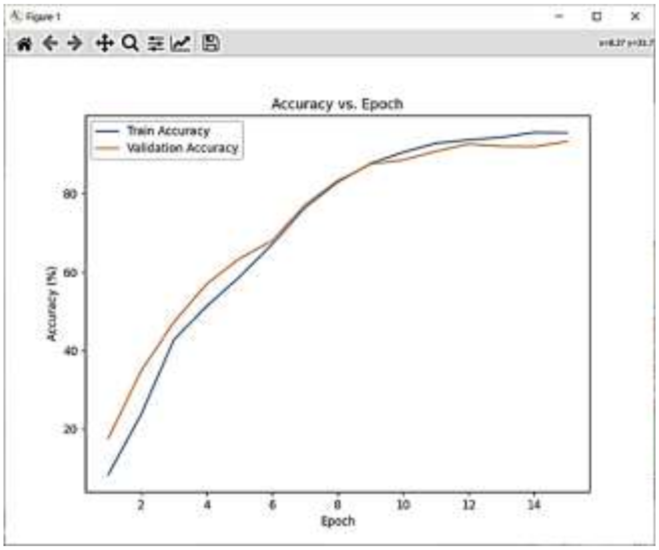

Fig. 12. *Result of recognizing Arabic handwritten characters with the convolutional neural network GoogLeNet*

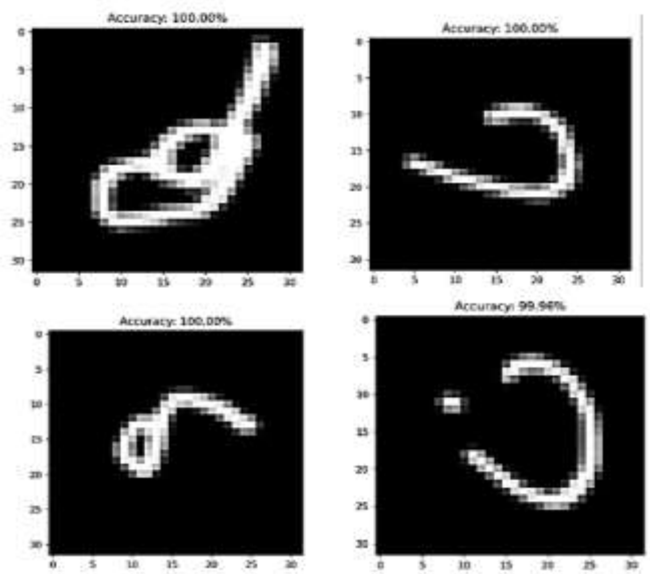

Fig. 13. *The example of recognizing handwritten Arabic characters with GoogLeNet*

In conclusion, the network demonstrates a steady growth in accuracy and reduction in losses during training, signifying successful model learning and its capability to produce good results on test data [13-20].

4. Results of Testing

After testing convolutional neural networks, it was found that the best results on this task of recognizing handwritten Arabic characters were shown by VGG19.

VGG19 demonstrated the best recognition results for handwritten Arabic characters after 15 epochs of training and showed 94.5%.

This was achieved due to some properties inherent to VGG19, which make it unique, namely: VGG19 is a deep architecture consisting of 19 layers, enabling it to learn complex functions and patterns in the data.

Deeper networks can capture more intricate hierarchies of features, aiding the network in recognizing finer image details.

VGG19 employs relatively small 3×3 convolutional filters throughout the network. The use of these smaller filters repeatedly accumulates nonlinearities, allowing the model to effectively capture both local and global patterns.

The architecture of VGG19 is simple and uniform. It employs a stack of small-sized convolutional layers followed by max-pooling layers. This simplicity facilitates understanding and implementation. The utilization of weight sharing in the convolutional layers assists the model in generalizing better and learning features that are invariant to minor transformations in input data.

The results of the testing are shown in Table 1.

The results for the LeNet model were examined. The highest accuracy (98.60%) was achieved for the class خ, indicating its ability to effectively recognize this class. The lowest accuracy (86.35%) was observed for the class ة, indicating difficulties in recognizing this particular class. In some instances, such as for the classes ب (99.99%) and ص (98.80%), the LeNet model exhibited similar results.

The outcomes of the AlexNet model were investigated. The maximum accuracy (100%) was reached for the classes' ك and ل. The lowest accuracy (72.03%) was associated with the class س, indicating challenges in its recognition. For certain classes like ع (96.34%) and ق (98.70%), the accuracy was approximately similar.

An analysis was conducted on the results of the VGG19 model. The highest accuracy (99.99%) was achieved for the classes' خ, ش, and ص, showcasing its proficiency in recognizing these classes. For the class ز, the accuracy was a mere 0.09%, reflecting difficulties in its recognition. In several instances, such as ط (99.28%) and ظ (21.36%), the accuracy was roughly consistent.

The results of the ResNet model were examined. The highest accuracy (99.97%) was attained for the classes' خ and م, signifying its successful recognition of these classes. For the class د, the accuracy was only 4.45%, highlighting challenges in its recognition. In certain cases, such as ت (99.85%) and د (4.45%), the accuracy was approximately similar.

The results of the GoogLeNet model were analyzed. The highest accuracy (100%) was achieved for several classes, including خ, س, ش, ص, and others. For the classes' ز and ج, the accuracy was relatively low, indicating difficulties in their recognition.

Table 1: Result of testing every single CNN model

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Arabic symbols	LeNet	AlexNet	VGG19	ResNet	GoogLeNet
ا	100%	100%	99.83%	100%	100%
ب	99.99%	83.63%	99.99%	30.36%	100%
ت	99.80%	99.55%	4.32%	99.85%	98.79%
ث	86.35%	2.06%	98.59%	70.06%	96.99%
ج	65.65%	32.51%	99.90%	21.80%	10.39%
ح	98.60%	50.12%	66.71%	99.84%	99.42%
خ	99.99%	100%	94.25%	99.97%	99.99%
د	96.40%	85.62%	72.34%	4.45%	93.34%
ذ	99.99%	41.30%	65.58%	98.19%	99.78%
ر	99.99%	100%	0.18%	99.48%	99.98%
ز	48.84%	13.62%	98.93%	24.85%	0.09%
س	95.88%	100%	99.99%	99.92%	100%
ش	99.86%	100%	99.99%	99.87%	97.45%
ص	98.80%	99.57%	99.99%	100%	99.76%
ض	99.95%	100%	100%	99.99%	97.69%
ط	75%	99.99%	99.28%	99.03%	99.98%
ظ	99.35%	99.11%	21.36%	99.96%	16.07%
ع	99.84%	96.34%	9.45%	99.89%	99.68%
غ	12.26%	100%	80.72%	98.70%	100%
ف	96.74%	98.66%	99.54%	99.74%	91.77%
ق	72.03%	98.70%	84.83%	74.60%	73.55%
ك	100%	100%	91.86%	100%	100%
ل	100%	100%	99.81%	99.96%	100%
م	100%	100%	47.45%	100%	100%
ن	100%	100%	29.87%	100%	99.96%
ه	100%	100%	77.68%	100%	100%
و	99.85%	96.21%	100%	99.95%	100%
ي	98.20	100%	100%	100%	100%

5. Conclusion

Among the considered models, GoogLeNet stood out with its high accuracy across many classes. Its versatile and complex architecture enabled more effective representation and analysis of diverse patterns.

In conclusion, GoogLeNet demonstrated the best results with high accuracy across the majority of classes. While the other models also displayed strong performance, they exhibited variations in accuracy based on class distinctions and architectural nuances.

Considering the task of recognizing handwritten Arabic characters, the comparison suggests that GoogLeNet is the most promising candidate for achieving accurate and consistent results. Its superior performance in terms of both training and validation metrics makes it a strong contender for effectively addressing the challenges posed by this specific task.

Overall, the prospects for work in Arabic character recognition using convolutional neural networks are extensive. Advancements in technologies and methods in this field could lead to the development of more accurate, flexible, and multifunctional Arabic text recognition systems.

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