Deep Learning Techniques for Fine Motor Skills Assessment in Preschool Children

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Abstract: - Fine motor skills are abilities that involve fine motor control, dexterity and precision usually involving hands and eyes coordination, increasing peoples' self-reliance and self-esteem in everyday activities. Convolutional Neural Networks (CNN) are considered suitable and can be used to classify images with great accuracy. This study aims to evaluate preschool children fine motor skills, using the proposed *MotorSkillsCNN* model trained with drawings of Greek pupils in public Kindergarten schools. The training of the proposed CNN model is based on Griffiths II Hand and Eye Coordination Scale. A unique dataset that consists of 884 images of children's drawings, that represent a man or a woman, is structured at this study and evaluated by experts, shaping the labels of the classes to be used by the proposed model. The results showed that automatic detection of fine motor skills is a hard work but is feasible

Key-Words: - Convolutional Neural Networks, Deep Learning, Fine motor skills, Griffiths test, Preschool

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1 Introduction

Psychomotor development refers to changes in a child's cognitive, emotional, motor, and social capacities from the beginning of life, regulated by the education or environmental stimuli that children receive [1]. In particular, motor development is distinguished into gross motor and fine motor skills development. Gross motor skills are movements that involve large muscle groups such as walking and running, while fine motor skills involve manual dexterity and precision and often require coordinating activities of the hands and fingers with the eyes such as writing. Over time, these skills advance and soon, drawings, expand children's ways of exploring, expressing and coming to terms with the world they inhabit in a structured and enjoyable manner. Particularly, fine motor skills typically develop during the preschool period when most children possess a sufficient range of skills for coping with the basic environmental demands that require behavioural adjustment [2].

Thus, early identification of motor coordination difficulties and comprehension of how risk factors evolve as a child is growing, are particularly important to target early intervention and ensure that children reach their full developmental potential [2], [3]. Screening tests are practical tools that allow unbiased developmental evaluation, guaranteeing at the same time the early detection of possible deviations from typical development [4].

One of the best-known screening developmental test is the "Griffiths Scales No II". It is an internationally acknowledged and reliable method for the assessment of development, consisting of six sub scales.

The major advantage is that every scale can give a different developmental quotient and provides a clear diagnostic indication in early childhood. Griffiths at 1984 stated that: each subscale was devised to be a separate and complete scale, measuring only one aspect of learning or process of development, and measure this aspect thoroughly[5].

Thus, the Griffiths Scales could be a useful tool for early assessment of developmental delays [6].

Teachers role in monitoring the development of children's motor skills in school is as important as the role of parents at home. Teachers must be able to observe children's growth, evaluate their pace of progress, and apply strategies and practices to motivate their motor development. Understanding the motor skills profile is very important for teachers because the activities in which children engage can affect their next stage of learning, including their writing ability, which is considered a vital skill in the learning process. Unfortunately, there are relatively few qualified teachers who can identify children's motor developmental delays [7].

However, many teachers and students have begun to examine a variety of technological applications for supporting educational demands, taking advantage of all digital forms of learning, such as e-learning, distance learning and m-learning [8]. Despite the rapid technological development, possibilities of methodological data processing regarding the prediction of children's physical activity and motor development are limited [9].

Deep learning (DL) is a subfield of Machine learning (ML). The "deep" in DL comes from the hidden layers that are built into the DL models, which are typically neural networks. One of the names that DL has gone by is Artificial Neural Networks (ANNs). ANNs are known as universal function approximators because they are able to learn any function, no matter how complicated, with just a single hidden layer. Therefore, one hidden layer or more hidden layers refer to one or more layers between input and output data in an algorithm. When an ANN has two or more hidden layers, it is called deep neural network (DNN). DL, as a new generation of ANN [10], is in the intersections among the research areas of neural networks, artificial intelligence, graphical modeling, optimization, pattern recognition, and signal processing [11]. Convolutional Neural Networks (CNN) are signifigant part of DL algorithms providing great abilities to represent complex relationships between images (input) and image classes (output data) [12]. CNN is one of the most popular DL approaches in the field of graphic processing as it performs well in image processing and directly deals with raw images [13]. Therefore, CNN is a powerful algorithm, used for analysis of visual imagery and for performing tasks such as detection, recognition, segmentation, and classification of image's features [14],[15],[16].

To our knowledge, only few studies [17], [18], [19], [20] have employed CNN models to predict motor skills in children and adolescents. Although the aforementioned studies indicate that ML approaches are feasible and offer enhanced accuracy for accelerometry-based assessments of motor skills in school-aged children and adolescents, the validity of neural networks developed in preschool-aged children has not been investigated, with only one recent exception [9].

Additionally, previous research in school-aged children and adolescents has used models with Multi-Layer Perceptron Networks (MLPs) or Deep Learning Ensemble Network (DLEN) approaches [17], [18], [19]. Finally, besides the aforementioned shortcomings, no single model used has been compared to a 'typical' Developmental test [21], leaving no indication that deep learning models can help and complement traditional assessments.

2 Methodology

Thus, the purpose of this study is to fill the research gap, which concerns the study of methods assessing fine motor skills in preschool children, using deep machine learning techniques.

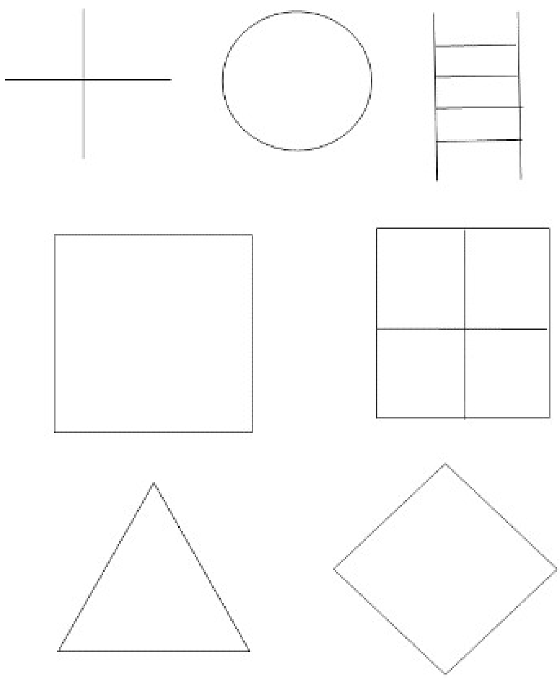

Figure 1: Griffiths II test geometrical shapes

Five hundred children aged 4–6 years (48-72 months) were recruited to participate in the study from Greek public schools in Northern Greece. Griffiths II Scale D (eye–hand co-ordination) that consists of items such as building a tower of cubes, cutting with scissors, copying simple geometrical shapes (Figure 1), drawing pictures of a house and a person (freely) and threading beads on a lace, was used as a study tool [6].

Test score was transformed into developmental age (DA). There are six items for each year in scale D. Items passed successfully are multiplied by two and the results give the Developmental Age score in months. The success gives the performer a symbol of + counter to – that represents failure [6]. For example, figure 2 shows shapes and picture (little man) drawn by a child of 37 months old (about 3 years old). The child in the example draws more complex geometrical shapes expected for his or her own chronological level. This means that this child (DA 60 months) is well above the average age on fine motor scale and 23 months (almost 2 years) above its Chronological Age.

Figure 2: Drawings of a 3-years-old child (37 months old) with DA 60 months

The score depends on the number of the skills to succeed not the order in which they were performed. Test's application to children should start with skills that correspond to younger age than their chronological and stop after 6 consecutive failures in 6 different skills.

Table 1: Griffiths test scores and classes according to Developmental Age

DA	Class
32-47	0
48-53	1
54-61	2
62-67	3
68-73	4
74-150	5

The definition of each class was suggested by experts in the field and according to Table 1, six different classes were formed depending on the grade that the kids got in the shapes and drawings they were asked to implement according to Griffiths test II (see Figure 2). Figure 3 includes a description of the planned research implementation. Shapes and drawings were assessed [2] and classified into 6 different categories.

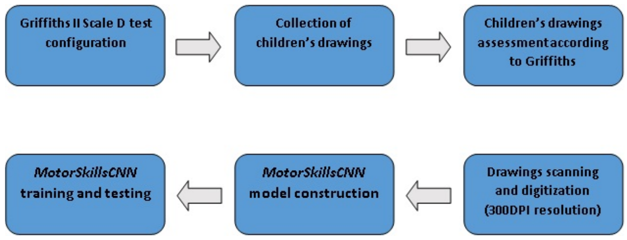

Figure 3: Research implementation

3 Dataset

In order to understand children's drawing behaviours a dataset that consists of 884 images that represent a man or a woman is introduced at this study. The drawing selected by 20 preschool units and 442 children draw a man and a woman.

Three educational experts decided on the score to be assigned to each drawing and assigned classified labels accordingly Table1.

The dataset was divided into training and test sets where 802 drawings where used for the CNN model training and the rest 82 drawings (9%) where used as test set. Figures 4 and 5 represent samples of drawings for class 0 and class 5 accordingly.

Figure 4: Drawing sample of class 0

4 The *MotorSkillsCNN* model

A CNN model is a multilayer stacked neural network, involving linear and nonlinear operations between the different layers. Representative features are extracted from the input data, through the convolution layers, the activation functions, the pooling layers and finally the classification is achieved by a multilayer perceptron. [4]. The deep learning *MotorSkillsCNN* model,

Figure 5: Drawing sample of class 5

that developed for this study, was applied on the training set (see Figure 6) in order to provide a final model capable to classify the drawings of the children according to Griffiths test.

The structure of the *MotorSkillsCNN* model (Figure 6) consists of:

- 3 convolution layers with 64 convolution filters of 3x3 kernels.
- Max-pooling layers between convolution layers, that helps to reduce the spatial size of the convolved features.
- One flatten layer that converts the data into a 1-dimensional array of 186624 elements for input to the next layer.
- A dense layer of 64 neurons.
- The output layer of 6 classes.

The ReLU activation function is used between convolution and dense layers of *MotorSkillsCNN*, to prevent the exponential growth of computational cost that is required to operate the convolutional neural network.

All possible combinations with the following structures were tested to decide the final model, a) number of Convolution layers = [1, 2, 3], b) number of filters per convolution layer = [32, 64, 128] and c) number of dense layers = [1, 2, 3]. For each layer combination, the model's output was compared with Griffiths II real scores, in order to select the most effective model. Finally the structure of the most effective model is comprised of three Convolution layers with 64 filters per convolution layer and 3 dense layers. The accuracy index is used as a measure to test model's classification ability across all layer's combinations and is formed as Equation 1:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

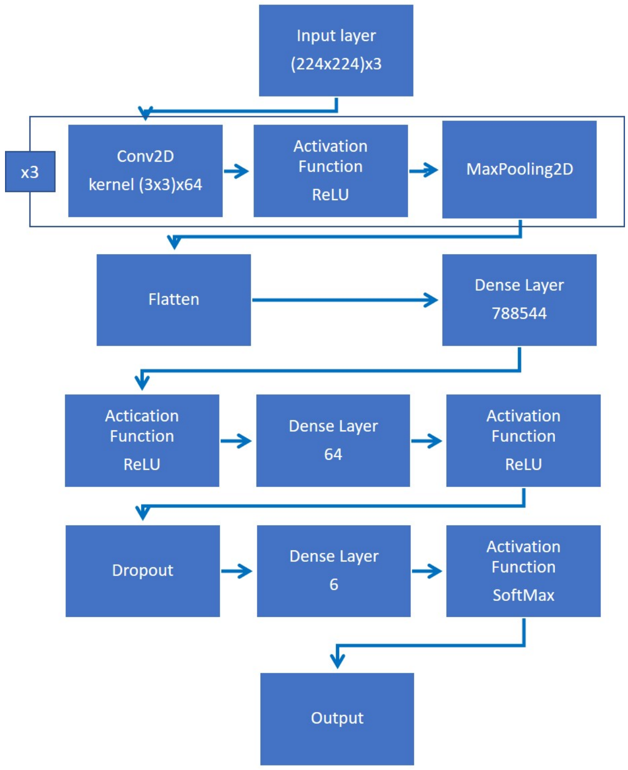

Figure 6: The basic structure of the *MotorSkillsCNN* model

where:

- TP (True Positive) represents the number of true positive instances,
- FP (False Positive) represents the number of false positive instances,
- FN (False Negative) represents the number of false negative instances and
- TN (True Negative) represents the number of true negative instances.

5 Results

The training accuracy per epoch for the introduced *MotorSkillsCNN* model is presented in Figure 7.

It is observed that the dataset accuracy is close to 1 after 14 epochs indicating that the model is well trained. The loss function that used to improve the prediction capability of *MotorSkillsCNN* model, is the sparse categorical cross-entropy (L_{CE}) that is proposed for multiclass classification problems and is defined as Equation 2:

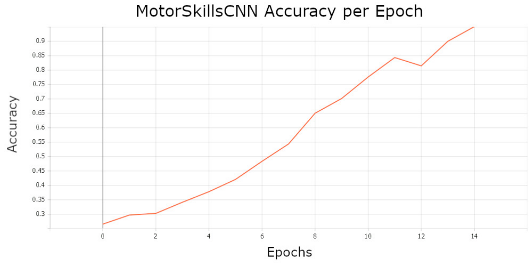

Figure 7: *MotorSkillsCNN* training accuracy per epoch

$$L_{CE} = -\sum_{i=1}^{N} t_i \log(p_i) \quad (2)$$

where t_i is the truth label and p_i is the Softmax probability for the i_{th} of N classes. The results of L_{CE} during training are presented at Figure 8, where 14 epochs are enough to minimize the loss by giving a L_{CE} value close to zero, indicating a well-trained model.

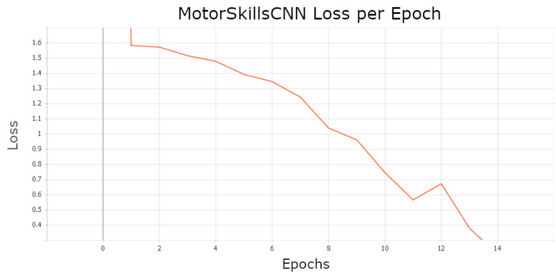

Figure 8: *MotorSkillsCNN* loss function (L_{CE}) per epoch during training

The accuracy of the *MotorSkillsCNN* model for all class's prediction is equal to 0.37. This fact at first glance indicates a low performance of classification. However, this accuracy can be considered satisfactory if one focus at the class distribution predicted by the model in the confusion matrix at Table2. According to this table, the classes with more images in the test set, show a higher classification performance. For example, at the fifth class it is observed that 12 out of the 26 drawings were classified correctly, 3 were placed in the next class, 8 in the previous class and 3 were classified two classes back. We consider that if the dataset is increased, the performance of the model will be definitely improved.

Classes could be merged to improve accuracy, but it was preferred to study the performance of the 6-class model that we believe best represents better the groups of children being studied. This study an initial approach applied to the unique dataset that collected from preschool children in order to classify and identify on time children's fine motor skills.

Table 2: Confusion matrix of test set (Columns reffer to predictive values and rows to actual values respectively)

	C0	C1	C2	C3	C4	C5
C0	0	0	0	1	2	0
C1	0	3	1	0	3	0
C2	0	0	4	6	4	2
C3	0	1	3	8	4	4
C4	0	0	3	8	12	3
C5	0	1	0	2	4	3

6 Conclusion

An innovative deep learning model called *MotorSkillsCNN* was developed in order to identify fine motor skills of preschool children. A new dataset of 884 drawings for fine motor skills identification was also developed at this study and a scaling of 6 class motor skills discrimination was implemented. The performance of the proposed CNN method gives significant results that can be improved by larger datasets. Fine motor skills measuring is very important in early children's education. Deep learning and particularly the model proposed will be able to help teachers and parents achieve a fast and easy fine motor skills assessment of their children through the simple process of feeding the model with specific drawings. This research will proceed with the collection of more drawing by kindergarten children in Greece in order to enhance the model's accuracy. A next step is the comparison of *MotorSkillsCNN* with other well-known pre-trained models.

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Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Author Contributions: Please, indicate the role and the contribution of each author:

Kostantinos Stikas and Paraskevi Giagazoglou with their team carried out the collection of children's drawings and decided on the score to be assigned to each drawing.
Alkiviadis Tsimpiris was responsible for the construction of the CNN model.
Apostolos Valiakos has organized and executed the training and testing of the deep learning model.
Dimitrios Varsamis has evaluated the results.