**Transactions on Engineering and Computing Sciences - Vol. 11, No. 5**
**Publication Date: October 25, 2023**
**DOI**:10.14738/tecs.115.15441.
Kika, A., Dashi, F., & Alimehmeti, R. (2023). Graph Convolutional Network Approach for Predicting the Severity of Carpal Tunnel Syndrome. Transactions on Engineering and Computing Sciences, 11(5). 38-44.

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# Graph Convolutional Network Approach for Predicting the Severity of Carpal Tunnel Syndrome

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## ABSTRACT

**This study proposes a framework based on graph convolutional network to predict the severity of carpal tunnel syndrome. The data of 100 patients diagnosed and treated for carpal tunnel syndrome (CTS) were included in this study resulting in 164 operated hands. The collected data include patient generalities, data from the clinical examination of the stage of CTS, electrophysiological study (EPS) and the data from BCTQ questionnaire. The data was prepared for modelling the graph. A weighted graph that stores not only the features of each case but also the relationship between the cases is created. We compared the model accuracy of graph convolutional network to different machine learning algorithms. The results showed that this model achieves higher result of 90 % accuracy.**

**Keywords:** graph, graph convolutional network, deep learning, carpal tunnel syndrome.

## INTRODUCTION

Carpal tunnel syndrome (CTS) is the most frequent entrapment neuropathy of the upper extremity. It occurs due to compression of the median nerve in the carpal tunnel, which causes functional disability of the hand. CTS affects 14.4 % of general population [1]. Higher prevalence rates of CTS have been reported in certain occupations [1], that necessitate repeated movement in flexion-extension of the wrist and fingers. In general population there was a 0.7% prevalence of undiagnosed CTS with severity like that of patients undergoing surgery [2]. There are several factors that contribute to clinical gravity of CTS related to different clinical conditions or predisposing movements/gestures related to the professional environment. The determination of the factors that contribute to the severity of this syndrome are essential to predict, prevent CST and provide appropriate treatment in different stages of this clinical condition.

The rest of the paper is structured as follows. “Related work” section reviews some of the reported studies that used artificial intelligence techniques in prediction in medicine focusing

more on carpal tunnel syndrome and advantages of graph neural techniques followed by "Methodology and data" section where we present the data source and its features as well the methodology and algorithms that are used for prediction. In "Experimental settings and Results" section, we present experimental analysis and evaluate empirically the proposed models. The conclusions and future work are summarized in "Conclusion" section.

## RELATED WORK

Artificial Intelligence methods and techniques have been used recently to classify and diagnose carpal tunnel syndrome. In [3] a machine learning model that predicts the probability of a patient improving after the hydro-dissection injection process based on the aggregated data after three different months (one, three, and six) has been proposed. In [4] five machine learning techniques (Logistic Regression (LR), SVM, KNN, Decision Tree (DT), and Naive–Bayes (NB)) were used to examine and to investigate the possibility of automatic detection, based on electrodiagnostic features, for the median nerve mononeuropathy and decision making about carpal tunnel syndrome. The most accurate classifier (SVM) achieved an accuracy of 0.9513 showing the ability of automated identification of carpal tunnel syndrome. The ultrasonography images were used in a deep and transfer learning system for the detection of cubital tunnel syndrome (CuTS) [5]. The highest score had an accuracy of 0.90, a precision of 0.86, and an F-measure of 0.92. The proposed technique enables the accurate prediction of CuTS without the need to measure CSA. The machine learning methods that are used in medicine for diagnosis and prognosis purposes often ignore the similarity of diagnoses, patient typology and the relationships that they have between each other. The method that are based on graph-data representation can cluster such similar patterns. Graph machine learning is used in the disease prediction domain by using two levels of graph analysis tasks: node classification and link prediction. In [6]a temporal graph for patient event sequences from electronic health records was constructed. The authors used a network-based approach to predict the probability of heart failure in individuals with chronic obstructive pulmonary disease pre-conditioning. In [7] a Graph Convolutional Network was used on a patient–disease bipartite graph to predict the link between patients and diseases. Alimehmeti et al. in [8] have studied the epidemiological distribution and the clinical-electric co-relation in carpal tunnel syndrome from 100 patients by using bivariate correlation analysis and the level of significance according to the Two-Tailed test of significance. This study showed that the syndrome is more frequent in women with BMI greater than 25 and in certain professions that request repetitive flexion of the grip. In order to create a model that can predict the severity of carpal tunnel syndrome these data will be reused and prepared for modelling a graph and training a graph convolutional network. To our knowledge, no studies used graph neural deep learning approaches to predict the severity of carpal tunnel syndrome. This study presents a novel model based on graph neural network deep learning techniques that can be used to predict the severity of carpal tunnel syndrome.

## METHOTOLOGY AND DATA

The data were collected from 100 patients referred for carpal tunnel syndrome. They have undergone surgery on one or both hands over time resulting in 164 hands operated for this syndrome. The data consisted of generaties of the patients, clinical examination of the stage of CTS, electrophysiological study (EPS) and the results of Boston Carpal Tunnel Syndrome

Questionnaire (BCTQ). The Boston Questionnaire was developed by Levine et al. [9] at the Brigham and Women's Hospital as an assessment tool for clients with carpal tunnel syndrome. BCTQ is a valid, reliable, responsive and acceptable instrument [10].

Gori et al. in [11] proposed a novel neural network model capable of processing graph structure data, graph neural network. A graph can be represented as G = (V, E, W) where V represents the set of N nodes, E denotes the set of edges connecting these nodes and W is the adjacency matrix. The adjacency matrix describes the connections between any two nodes in V.

The data were prepared for modelling the graph neural network. The data contain information about each patient: sex, age, residence (city or country), level of education, BMI, time lapse from diagnosis to surgery, and for right- and left-hand questionnaire points category, clinical examination stage and electrophysiological stage. The nodes of the graph represent the case and each node has as its feature vector the data of the patient. A link Lijn between node i and node j is added to the graph if the patient i has the same value for attribute n as the patient j.

We construct a graph with 164 nodes and 26299 links between source nodes and target nodes for each hand.

Since the number of links is very high in order to understand the common features that are important in prediction a slight modification in the first graph is made to create a weighted graph: for each node Ni we find the node Nj which has the maximum number of equal features; the link between them is added to a new graph and the weight of the link is the number of equal features. In figure 1 the representation of this graph that shows the link between nodes which have the higher number of equal features is shown:

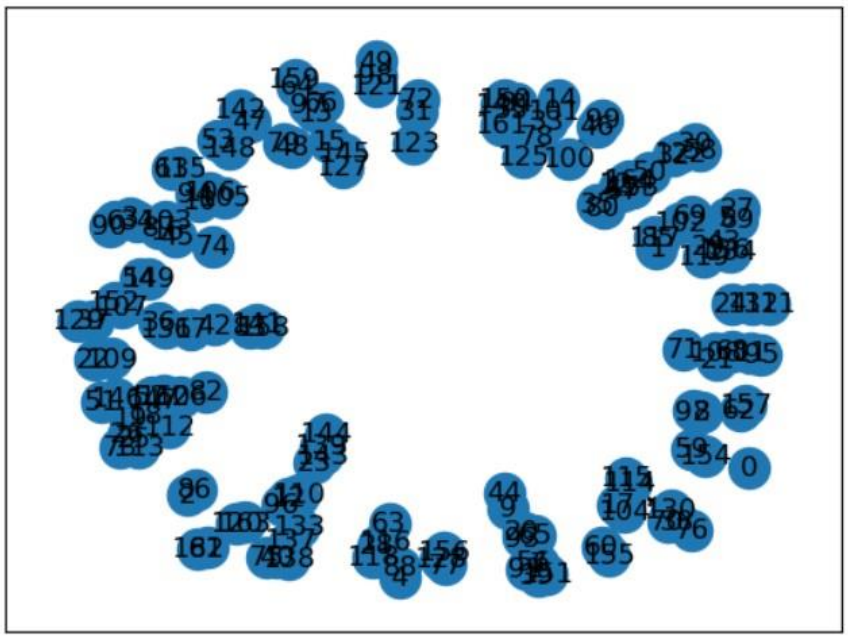


**Figure 1: The graph that shows connections between the nodes that have highest number of equal features.**

Each node represents a case and keeps the features of the patient and on the other hand it has an weighted edge to another node if they share the highest number of common features. The weighted graph has the capacity to extract the latent relationship among the different cases. In order to aggregate the information between two neighbor nodes one powerful deep learning tools will be used: Graph Convolutional Network (GCN).

The graph convolutional network (GCN) model was proposed by Kipf and Welling [12]. The values of the features of each node were aggregated along with the values of the features of the neighbor nodes.

Each layer of CGN will use aggregation of the neighbor nodes values as inputs for the next layer. In matrix form graph convolution, the next layer will be formed using formula 1.

$$Vl=\sigma(\check{D}\text{-}1/2\check{A}\ \check{D}\text{-}1/2\ Vl\text{-}1Wl\text{-}1) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

In this formula:
Vl the representation of features in l layer in the form NXM (N nodes with M features)
σ is an activation nonlinear function
$\check{A}=A+IN$
A is the adjacency matrix of the undirected graph, IN is the identity matrix
$\check{D}$ is the degree of matrix $\check{A}$, $\check{D}ii = \sum j\ \check{A}ij$

and Wl is a layer specific trainable weight matrix that project features to another space

Through this equation the dimension of the graph will be reduced until we will reach NX4 dimension. We have four classes for the classification of the severity of carpal tunnel syndrome. A SoftMax function will be applied in order to get probability for each class.

Our GCN-based model will be compared as baseline with four some known classifier, namely decision tree C4.5 algorithm (J48 in Weka), Random Forest, Naïve Bayes and Support Vector Machine. C4.5 is information gain-based algorithm developed by Ross Quinlan. This algorithm splits continuous attributes into two groups at a split point that minimizes the expected information requirement [13]. Naïve Bayes is based on Bayes' Theorem with an assumption of independence among predictors. Random Forest are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest[14]. Support Vector Machine finds a hyper-plane that separates the different types of data [15].

## EXPERIMENTAL SETTINGS AND RESULTS

Machine learning models will be created and evaluated by using Waikato Environment for Knowledge Analysis (WEKA), which is an open-source software developed at the University of Waikato, New Zealand. WEKA is a collection of machine learning algorithms that supports data mining tasks by providing a wide range of tools that can be used for data pre-processing,

classification, clustering, regression, association and visualization [16]. We randomly divide the dataset into training, validation and test sets in a 0.80:0.10: 0.10 ratio.

In table 1 the evaluation experiments are summarized.

**Table 1: Performance of machine learning models**

| Method | Accuracy | Precision | Recall | F_Measure |
|---|---|---|---|---|
| J48 | 86.58 | 0.80 | 0.86 | 0.78 |
| RandomForest | 85.36 | 0.83 | 0.85 | 0.84 |
| Naïve Bayes | 76.21 | 0.75 | 0.76 | 0.75 |
| Multilayer Percepton | 84.14 | 0.83 | 0.84 | 0.73 |

As we can see from these results the best accuracy is reached by J48 algorithm followed by Random Forest.

The graph and Convolutional graph network is modeled and trained by using PyTorch Geometric (PyG), a geometric deep learning extension library for PyTorch [17] which achieves high performance by leveraging dedicated CUDA kernels [18].

We took in consideration and adjusted several hyperparameters in GCN model such as the number of layers, the learning rate of the optimizer, the total training epochs and dropout. We trained the model for a maximum of 200 epochs. By adjusting the parameters empirically, we trained the models using Adam optimizer [19] with a learning rate of 0.01. We applied a three-layer model, a hidden size of 16 units and ReLU activation function for hidden layers in GCN architecture and followed by a SoftMax activation function for classification.

In the figure 2 the results from the training process for 31 first epochs are presented. In the next following epochs, the model didn't improve reaching the maximum accuracy of 0.9091.

Epoch: 001, Loss: 1.4174, Accuracy: 0.7273
Epoch: 002, Loss: 1.3324, Accuracy: 0.7273
Epoch: 003, Loss: 1.2846, Accuracy: 0.7273
Epoch: 004, Loss: 1.3628, Accuracy: 0.7273
Epoch: 005, Loss: 1.2232, Accuracy: 0.8182
Epoch: 006, Loss: 1.2123, Accuracy: 0.8182
Epoch: 007, Loss: 1.1971, Accuracy: 0.9091
Epoch: 008, Loss: 1.0866, Accuracy: 0.9091
Epoch: 009, Loss: 1.1765, Accuracy: 0.9091
Epoch: 010, Loss: 1.0564, Accuracy: 0.9091
Epoch: 011, Loss: 1.1022, Accuracy: 0.9091
Epoch: 012, Loss: 1.0580, Accuracy: 0.9091
Epoch: 013, Loss: 1.0193, Accuracy: 0.9091
Epoch: 014, Loss: 1.0557, Accuracy: 0.9091
Epoch: 015, Loss: 1.1123, Accuracy: 0.9091
Epoch: 016, Loss: 1.0714, Accuracy: 0.9091

Epoch: 017, Loss: 1.1067, Accuracy: 0.9091
Epoch: 018, Loss: 1.0269, Accuracy: 0.9091
Epoch: 019, Loss: 1.0381, Accuracy: 0.9091
Epoch: 020, Loss: 0.9952, Accuracy: 0.9091
Epoch: 021, Loss: 0.9866, Accuracy: 0.9091
Epoch: 022, Loss: 0.9431, Accuracy: 0.9091
Epoch: 023, Loss: 1.0181, Accuracy: 0.9091
Epoch: 024, Loss: 1.0543, Accuracy: 0.9091
Epoch: 025, Loss: 0.9716, Accuracy: 0.9091
Epoch: 026, Loss: 0.9362, Accuracy: 0.9091
Epoch: 027, Loss: 0.9132, Accuracy: 0.9091
Epoch: 028, Loss: 0.9364, Accuracy: 0.9091
Epoch: 029, Loss: 0.9616, Accuracy: 0.9091
Epoch: 030, Loss: 0.8788, Accuracy: 0.9091
Epoch: 031, Loss: 0.8558, Accuracy: 0.9091

**Figure 2: The results from the training process of CGN for the first 31 epochs**

## CONCLUSIONS

In this paper we proposed a graph convolutional network model for the prediction of carpal tunnel syndrome severity. The graph had 164 nodes which were created from the data of 100 patients. The connection between nodes represents the similarities between the features of the patient capturing the variety of latent relationships between them. The model performance was compared with several known classification machine learning algorithms: C4.5 algorithm(J48), Random Forest, Naïve Bayes and Support Vector Machine. Graph Convolutional Network had higher accuracy in predicting the severity of the tunnel carpal syndrome than the other models. In the future we plan to work with other kind of deep learning models with attention mechanisms such as graph attention network. The graph network deep learning models can help healthcare providers and researchers to better understand the features and the relationship between attributes of the patient in order to predict and prevent different kind of syndromes and diseases.

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