линии связи (Интернет, в том числе GPRS, и мобильную (сотовую) связь);

протоколы синхронного телеконсультирования по схеме «Мобильные сервисы+E-mail» (под мобильными сервисами мы понимаем обмен MMS/SMS сообщениями, мобильный Интернет и голосовую связь).

2. Первые результаты свидетельствуют о высокой эффективности ургентного телеконсультирования (быстрое получение консультации узкого специалиста, оптимизация оперативного лечения, увеличение объема помощи до личного приезда консультанта, улучшение результатов лечения).

3. Необходима разработка протоколов для догоспитального и госпитального синхронного телеконсультирования травмированных.

4. Малое количество проведенных ургентных телеконсультаций пока не позволяет нам провести строгое статистическое обоснование выработанных решений. Доказательная база синхронного телеконсультирования в травматологии и станет объектом нашего дальнейшего изучения.

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**THE FIRST POSITIVE EXPERIENCE OF THE USE OF URGENT SYNCHRONIC TELECONSULTATION IN TRAUMATOLOGY**

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Aim of the work – development of optimal scheme of usage urgent teleconsultation in traumatology at in-hospital stage, investigate first results. Its carried out 9 teleconsultations bya few technologies: scheme «MMS+E-mail», mobile telephony, mailing list, e-mail. Results. Optimal scheme of usage urgent teleconsultation in traumatology at in-hospital stage include: telemedical work stations on the base of mobile devices with digital cameras and alert-function (PDA, smartphones, communicators etc); communications lines (Internet, GPRS, mobile telephony); protocols for synchronous teleconsultations. The first results show the high efficiency of urgent teleconsultations (fast advicing of expert, optimisation of surgical treatment, increasing of medical care, good outcomes). It is necessary to develop protocols for pre- and in-hospital synchronous teleconsultations of injuried.

**Key words:** telemedicine, trauma, urgent care



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# IMPLEMENTING COMBINED NEURAL NETWORK MODEL FOR BREAST CANCER DIAGNOSIS

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**Abstract**

This paper illustrates the use of combined neural network (CNN) models to guide model selection for breast cancer diagnosis. Diagnosis tasks are among the most interesting activities in which to implement intelligent systems. Specifically, diagnosis is an attempt to accurately forecast the outcome of a specific situation, using as input information obtained from a concrete set of variables that potentially describe the situation. The CNN network model trained with Levenberg-Marquardt algorithm used the attributes of each record in the Wisconsin breast cancer database. The first level networks were implemented for the diagnosis of breast cancer using the attributes of each record as inputs. To improve diagnostic accuracy, the second level networks were trained using the outputs of the first level networks as input data. For the Wisconsin breast cancer diagnosis problem, the obtained total classification accuracy by the CNN network model was 98.15%. The CNN network model achieved accuracy rates which were higher than that of the stand-alone neural network models.

**Key words:** Combined neural network (CNN), Levenberg-Marquardt algorithm, Breast cancer diagnosis, Diagnostic accuracy

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### 1. INTRODUCTION

Medical diagnostic decision support systems have become an established component of medical technology. The main concept of the medical technology is an inductive engine that learns the decision characteristics of the diseases and can then be used to diagnose future patients with uncertain disease states. Neural networks have been used in a great number of medical diagnostic decision support system applications because of the belief that they have greater predictive power. Unfortunately, there is no theory available to guide an intelligent choice of model based on the complexity of the diagnostic task. In most situations, developers are simply picking a single model that yields satisfactory results, or they are benchmarking a small subset of models with cross validation estimates on test sets [1-3]. The economic and social values of breast cancer diagnosis are very high. As a result, the problem has attracted many researchers in the area of computational intelligence recently. They managed to achieve significant results varying from 95% to 98% [4-7] In this study, an application of the combined neural network (CNN) to the Wisconsin breast cancer diagnosis problem was reported. In order to implement CNN, for the first level models we used two sets of neural networks since there were two possible outcomes of breast cancer diagnosis (benign records and malignant records). Networks in each set were trained so that they are likely to be more accurate for one type of disorder than the other disorders. The predictions of the networks in the first level were combined by a second level neural network. We were able to achieve significant improvement in accuracy by applying neural networks as the second level model compared to the stand-alone neural networks.

Table 1.

Wisconsin breast cancer data[a]: description of attributes

| Attribute number | Attribute description | Minimum | Maximum | Mean | Standard deviation |
|---|---|---|---|---|---|
| 1 | Clump thickness | 1 | 10 | 4.44 | 2.82 |
| 2 | Uniformity of cell size | 1 | 10 | 3.15 | 3.07 |
| 3 | Uniformity of cell shape | 1 | 10 | 3.22 | 2.99 |
| 4 | Marginal adhesion | 1 | 10 | 2.83 | 2.86 |
| 5 | Single epithelial cell size | 1 | 10 | 3.23 | 2.22 |
| 6 | Bare nuclei | 1 | 10 | 3.54 | 3.64 |
| 7 | Bland chromatin | 1 | 10 | 3.45 | 2.45 |
| 8 | Normal nucleoli | 1 | 10 | 2.87 | 3.05 |
| 9 | Mitoses | 1 | 10 | 1.60 | 1.73 |

[a]N=683 observations, 239 malignant and 444 benign

### 2. WISCONSIN BREAST CANCER DATABASE OVERVIEW

Breast cancer is a malignant tumour that has developed from cells of the breast. Although scientists know some of the risk factors (i.e. ageing, genetic risk factors, family history, menstrual periods, not having children, obesity) that increase a woman's chance of developing breast cancer, they do not yet know what causes most breast cancers or exactly how some of these risk factors cause cells to become cancerous. Research is under way to learn more and scientists are making great progress in understanding how certain changes in DNA can cause normal breast cells to become cancerous [7]. In this study, the Wisconsin breast cancer database taken from fine needle aspirates from human breast tissue was analyzed. They have been collected by Wolberg and Mangasarian [7] at the University of Wisconsin-Madison Hospitals. The data consists of 683 records of virtually assessed nuclear features of fine needle aspirates taken from patients' breasts. Each record in the database has nine attributes. The nine attributes detailed in Table 1 are graded on an interval scale from a normal state of 1 to 10, with 10 being the most abnormal state. There are 239 malignant cases and 444 benign cases. A malignant label is confirmed by performing a biopsy on the breast tissue. Either a biopsy or a periodic examination is used to confirm a benign label.

### 3. COMBINED NEURAL NETWORK MODELS

CNN models often result in a prediction accuracy that is higher than that of the individual models. This construction is based on a straightforward approach that has been termed stacked generalization. The stacked generalization concepts formalized by Wolpert [8] and refer to schemes for feeding information from one set of generalizers to another before forming the final predicted value (output). The stacked generalization scheme can be viewed as a more sophisticated version of cross validation and has been shown experimentally to effectively improve generalization ability of artificial neural network (ANN) models over using stand-alone neural networks [2,3]. The multilayer perceptron neural networks (MLPNNs) were used at the first level and second level for the implementation of the CNN proposed in this study. This configuration occured on the theory that MLPNN has features such as the ability to learn and generalize, smaller training set requirements, fast operation, ease of implementation. In both the first level and second level analysis, the Levenberg-Marquardt training algorithm was used.

### 4. APPLICATION OF COMBINED NEURAL NETWORK TO WISCONSIN BREAST CANCER DATABASE

The CNN architecture used for the diagnosis of breast cancer is shown in Figure 1. ANN architectures are derived by trial and error and the complexity of the neural network is characterized by the number of hidden layers. There is no general rule for selection of appropriate number of hidden layers. Our architecture studies confirmed that for the diagnosis of breast cancer, a minimal network has better generalization properties and results in higher classification accuracy. The nine attributes detailed in Table 1 were used as the inputs of the MLPNNs employed in the architecture of CNN. For this data, MLPNNs with one hidden layer were superior to models with two and three hidden layers. The most suitable network configuration found was 20 neurons for the hidden layers and the number of output was 2. Samples with target outputs benign records and malignant records were given the binary target values of (0,1) and (1,0), respectively. In both the first level and second level, training of neural networks was done in 500 epochs since the cross validation errors began to rise at 500 epochs. Since the values of mean square errors (MSEs) converged to small constants approximately zero in 500 epochs, training of the neural networks with the Levenberg-Marquardt algorithm was determined to be successful.

The adequate functioning of neural networks depends on the sizes of the training set and test set. There are a total of 683 records in the Wisconsin breast cancer database, of which 444 benign records and 239 are malignant records. In the CNN, 250 of 683 records were used for training and the rest for testing. A practical way to find a point of better generalization is to use a small percentage (around 20%) of the training set for cross validation. For obtaining a better network generalization 50 training records were selected randomly to be used as a cross validation set. The training set consisted of 80 malignant records and 170 benign records. The testing set consisted of 159 malignant records and 274 benign records. The cross validation set consisted of 20 malignant records and 30 benign records. The test performance of the CNN was determined by the computation of the following statistical parameters:

*Specificity:* number of correct classified benign records / number of total benign records

*Sensitivity:* number of correct classified malignant records/ number of total malignant records

*Total classification accuracy:* number of correct classified records/number of total records

The CNN classified benign records and malignant records with the accuracy of 98.54% and 97.48%, respectively. The total classification accuracy was 98.15%. The correct classification rates of the stand-alone MLPNN were 92.34% for benign records, 91.19% for malignant records. Thus, the accuracy rates of the CNN model presented for this application were found to be higher than that of the stand-alone MLPNN.

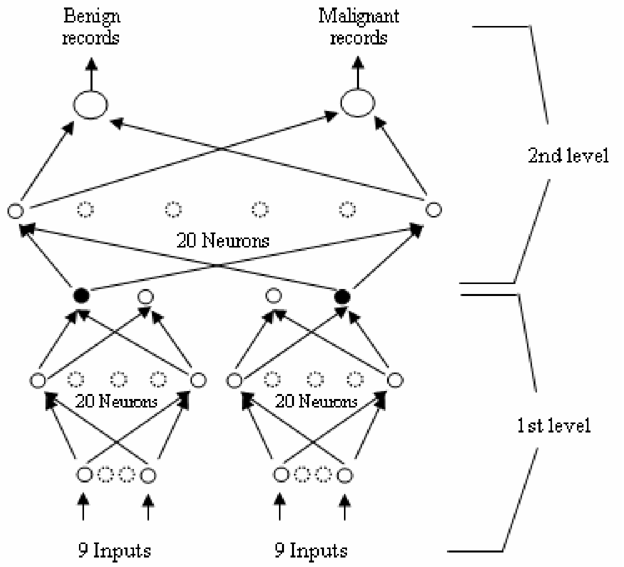


Figure 1.
The architecture of CNN

**5. CONCLUSION**

The classification results and the values of statistical parameters were used for evaluating performances of the classifiers. The conclusions drawn in the applications demonstrated that the CNN model provide a good distinction between classes.

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# ПРИМЕНЕНИЕ НЕЙРОСЕТЕВЫХ ТЕХНОЛОГИЙ В ЗАДАЧАХ ДИАГНОСТИКИ СКОЛИОЗА

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**Аннотация**

Одной из серьёзных патологий детей и подростков является сколиотическая деформация позвоночника. Для объективной оценки характера течения сколиотической болезни измеряют угол Кобба по рентгенологическим снимкам, и описывает кривизну дуги искривления. С целью уменьшения числа рентгенологических обследований больных сколиозом предлагается способ оптической регистрации изображения на основе нейросетевых технологий. Маркерные точки на опорных точках, выставляемые врачом автоматически распознаются системой и, далее по методике происходит обсчёт линейных и угловых величин между линиями, построенные на опорных точках. Данный метод предназначен для автоматизации процесса измерения и удобства ведения больных сколиозом, с целью наблюдения за динамикой изменения степени деформации позвоночника при лечении.

**Ключевые слова:** сколиоз, угол Кобба, Spinal pantograph, нейросети, сеть Хемминга, факторный анализ

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Сидячий образ жизни и увеличение нагрузок в учебной программе требует особого внимания к осанке подрастающего поколения. Одной из серьёзных патологий детей и подростков является сколиотическая деформация позвоночника, проявляющаяся искривлением во фронтальной плоскости и ротацией позвоночника вокруг своей оси.

Для объективной оценки характера течения сколиотической болезни нужна количественная мера, достоверно описывающая деформацию позвоночника. Такой общепринятой мерой, являющейся "золотым стандартом", служит угол Кобба [1], который определяется по рентгенологическим снимкам и описывает кривизну дуги искривления. Однако, рентгенологическое обследование позвоночника не безвредно для растущего организма ребенка. С целью уменьшения числа рентгенологических обследований больных сколиозом разработаны многочисленные неинвазивные методы, в том числе простейшие контактные методы: Spinal pantograph, flexible curve, body tracer [2, 3] и др. Один сеанс диагностики такими методами занимает около 15-20 мин, не считая времени для того, чтобы занести данные в карточку. И ещё какое-то время необходимо для постановки диагноза. Поэтому особенно актуальным является разработка автоматизированного комплекса неинвазивной диагностики, позволяющий автоматизировать процесс измере-