



شبكة المعلومات الجامعية
التوثيق الإلكتروني والميكروفيلم

بسم الله الرحمن الرحيم



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Computational Intelligence Method for Bones Classification and Abnormality Detection using X-ray Images

Thesis Submitted in Partial Fulfillment of the Requirements for the Degree
of PhD in Computer and Information Sciences

to

Department of Scientific Computing
Faculty of Computer and Information Sciences
Ain Shams University

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November – 2021
Cairo

Acknowledgment

First of all, I would like to thank **GOD** for his endless blessings, for giving me the power and strength to complete this work and for giving me supportive people.

I would like to express my deep gratitude to my supervisors who I'm lucky to work under their supervision, they are a family not only supervisors who always support me in my down times and believe in me. **Prof. Dr. Mohamed Tolba** (God bless him), for his usual support, patience, encouragement, guidance and care, **Prof. Dr. Howida Shedeed** for her usual support, motivation and guidance and **Dr. Manal Tantawi** the one who I am lucky to have by my side not only a supervisor but an elder sister too, I extend my utmost gratitude for your technical and scientific help, continuous supportive guidance in both technical and non-technical issues.

I would like to thank the world best gift, the most supportive family. I would like to thank **Dad** and **Mum** who have devoted themselves to support me in my whole life, not just this work for their endless passionate support and encouragement and the sleepless nights they spent to make it easier for me. And my sisters **Mahitab**, **Alaa** and **Esraa** for always being by my side in the downs and ups, they are the real meaning of "أَسْتَشْدُّ عَضْدَكَ بِأَخِيكَ". Thanks, my sisters for your usual moral support, motivation and being always by my side.

My family, thanks for being the shoulder I can always depend on and for constantly pushing me to become the person I want to become and create the life I want for myself. This thesis dedicated to you, to make you proud. Without you, everything is nothing.

I would also like to thank the world best friends **Yasmin Khaled**, **Ghada Hamed**, **Eman Hamdi**, **Alaa Atef**, **Alaa Salah** and **Reham El-Shahed** for always being by my side. Thanks for your constant encouragement in the most difficult times, for accepting me through the tough time. And a special thanks to my colleague **Bassel Safwat** for his usual motivation and technical support.

Last but not least, all those supportive people are around me till this moment except my **Dad**, the most supportive person in my life. I know that you were waiting this moment, I wish you were still here so I could make you proud.

Abstract

Wrong diagnosis for bone abnormalities may lead to serious side effects. Moreover, exhausted, and over loaded doctors may miss some cases. Hence, Computer aided diagnosis systems have a vital role nowadays.

Based on the conducted comparative analysis: 1) There is a lack of published datasets that can be used as benchmark due to the difficulty of collecting data from hospitals; 2) Most of the previous studies consider only one bone due to the high variability in the shape of different bone types and also due to lack of data; 3) Most of the existing studies don't consider the abnormality type; 4) Most of the previous studies apply the traditional methods for feature extraction and classification, except for few new studies that utilize deep learning models (CNN models); 5) The models used in deep learning based studies are of huge depth which increases the training time and computation. Hence, a computer-aided diagnosis (CAD) system based on deep learning approach is proposed to consider the drawbacks of the literature. Bones of the upper extremities: namely, shoulder, humerus, forearm, elbow, wrist, hand, and finger are considered. All experiments have been carried out using the MURA database, the largest public dataset of bone x-ray images.

In this work, three main approaches are proposed and examined: 1) one stage – one task approach; 2) one stage – two tasks approach; and 3) two stage – two tasks approach using state-of-art techniques. In the one stage – one task approach, the model takes the x-ray image as an input and outputs whether the bone is normal or not. While in the one stage – two tasks approach, the model takes the x-ray image as an input and outputs both the bone type and whether the bone is normal or not. Finally, in the two stage – two tasks

approach the classification is done through two stages. The first stage is to classify the bone type and the second stage is to detect whether the classified bone is normal or abnormal. Thus, in the second stage, each bone has its own classifier for abnormality detection. 10 different pretrained models have been examined for the three approaches. The results show the superiority of the two stage – two tasks approach. The best average sensitivity and specificity achieved by the first stage is 95.78% & 99.45% and 83.25% & 83.25% for the second stage, respectively. However, this approach utilizes very deep models which affect the performance and computation time.

Hence, a novel, reliable, hybrid, two-stage method for bone x-ray classification and abnormality detection is introduced. Growing Neural Gas (GNG) network is combined with eight models built from scratch and inspired from VGG model to achieve the best performance and least computations possible. The features extracted from GNG are fed into a two-stage classification step. The first stage classifies a bone X-ray into one of seven types, after which it is directed according to type to one of seven classifiers trained to detect bone abnormality. Hence, the classification step consists of eight different models: one for classification and seven for abnormality detection. The best average sensitivity and specificity obtained for the first stage is 95.86% and 99.63%, respectively. For the second stage, the best average sensitivity and specificity obtained is 92.50% and 92.12%, respectively. These results are superior compared to state of art pretrained models. In addition, the computation and processing time are significantly decreased by the proposed scheme. Furthermore, to the best knowledge of researchers, the proposed method is the first to integrate seven bones together in the same scheme. Finally, the hierarchical nature of the proposed method

allows considering two problems together: bone classification and abnormality detection.

List of Publications

- 1- Hadeer El-Saadawy, Manal Tantawi, Howida A. Shedeed, and Mohamed F. Tolba. "A Hybrid Two-Stage GNG–Modified VGG Method for Bone X-Rays Classification and Abnormality Detection,". IEEE Access, vol. 9, pp. 76649-76661, doi: 10.1109/ACCESS.2021.3081915, 2021. IF: 3.367.
- 2- Hadeer El-Saadawy, Manal Tantawi, Howida A. Shedeed, and Mohamed F. Tolba. "Hybrid Two-Stage CNN-SVM Model for Bone X-Rays Classification and Abnormality Detection,". International Journal of Sociotechnology and Knowledge Development (IJSKD), vol. 13, 2021.
- 3- Hadeer El-Saadawy, Manal Tantawi, Howida A. Shedeed, and Mohamed F. Tolba. "One-Stage vs Two-Stage Deep Learning Method for Bone Abnormality Detection." In: Hassanien A.E. et al. (eds) Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2021). Advances in Intelligent Systems and Computing, vol 1377. Springer, Cham. https://doi.org/10.1007/978-3-030-76346-6_12, 2021.
- 4- Hadeer El-Saadawy, Manal Tantawi, Howida A. Shedeed, and Mohamed F. Tolba. "Deep Learning Method for Bone Abnormality Detection Using Multi-View X-rays." In: Hassanien A.E. et al. (eds) Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2021). Advances in Intelligent Systems and Computing, vol 1377. Springer, Cham. https://doi.org/10.1007/978-3-030-76346-6_5, 2021.

- 5- Hadeer El-Saadawy, Manal Tantawi, Howida A. Shedeed, and Mohamed F. Tolba. “A Two-Stage Method for Bone X-Rays Abnormality Detection Using MobileNet Network,” In: Hassanien AE., Azar A., Gaber T., Oliva D., Tolba F. (eds) Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020). Advances in Intelligent Systems and Computing, vol 1153. Springer, Cham. https://doi.org/10.1007/978-3-030-44289-7_35, 2020.
- 6- Hadeer El-Saadawy, Manal Tantawi, Howida A. Shedeed, and Mohamed F. Tolba. “Bone X-Rays Classification and Abnormality Detection using Xception Network.” International Journal of Intelligent Computing and Information Sciences 21, no. 2 (2021): 82-95.

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