**Sports Risk Analysis using Data Mining Techniques**

**Section 1. Summary**

**1.1 References**

Jinling Zhengand **Chunyan Fan** (2022). Sports Risk Analysis Based on Knowledge Discovery and Data Driven\*.

Website: <https://doi.org/10.1155/2022/8589200>

**1.2 Purpose of study**

Sports are often the main physical education activity in schools, however almost all activities include some element of risk. Sports are more likely to result in accidents since they are practical activities. Therefore, a risk analysis for sports is necessary. Data analytics may be used to quantify the risk involved in sports. It will enable knowledge discovery of possible risks to college athletes using data-driven neural networks and help our investigation of risk involved in sports.

**1.3 Research design and strategy**

The author used multi-scale Attention ResNet model for estimating sports risk which uses attention Mechanism as described below.

**Attention Mechanism**

**Squeeze and Excitation Networks (SENet):**

By incorporating Squeeze and Excitation Modules, SENet clearly simulates the dynamic, nonlinear interdependencies between feature channels. By learning the weight distribution of each feature channel and then extracting the key features channel based on weights, the Se module will remove unnecessary and redundant features. The feature map is improved by the module via squeezing and excitation techniques.

**Squeeze Operation:** convolution kernel uses local receptive filed values and ignore other values to participate in the operation.

**Excitation Operation:** The total correlation between channels may be derived using the channel aggregate data gathered in the preceding phase. Non-linear and mutually exclusive interactions must be able to be identified by the excitation operation. To fulfill the criteria during the excitation operation, the ReLU function is employed as the activation function in a simple sigmoid gating mechanism. Two completely linked layers are introduced before and after the ReLU function to simplify the model and broaden its applicability. Run the output via the dimensionality reduction layer with a dimensionality reduction ratio of r, the ReLU activation function, and lastly the dimensionality raising layer to transform the output to HxWxCxU, to maintain a constant channel size. To obtain the normalized feature channel weights, the excitation operation's output is scaled using the Sigmoid function. The weight distribution of the feature channels, which is a byproduct of the excitation process, is multiplied by the correlating feature channels to produce the recalibrated attention feature map.

**Convolutional Block Attention Module (CBAM):** It is a lightweight general module. The main purpose of the CBAM and SE modules is the same, and their difference is that CBAM uses both maximum pooling and average pooling. And it generates weights through the information of two dimensions of feature channel and space and realizes the re-calibration operation of the original feature. The spatial attention module is primarily utilized as a supplement to the channel attention module to get the spatial location of significant features and to realize the description of the spatial correlation between features. When calculating the spatial attention feature map, it is first necessary to aggregate the channel information of the feature map along the axis of the feature channel through the max pooling and average pooling operations to generate two sets of feature descriptors. This represents the max-pooled feature and average-pooled feature of the feature channel, respectively. The two feature maps are then concatenated and passed through a standard convolutional layer to generate a spatial attention feature map, which encodes the spatial location of reinforcement or suppression.

**Multi-scale Attention ResNet:**

A convolutional layer plus a pooling layer makes up the initial section of the multiscale attention ResNet (MSAR). The input feature map of the multiscale residual module is created after the short-term features in the original data are retrieved using 64 large-size 32x1 convolution kernels. Each layer of the multi-scale residual attention module is composed of three groups of residual modules and attention modules. There are two identical convolutional layers in each residual module. After each residual module, the attention module is attached to change the feature response's weight distribution and boost its expressive power. The SE module and the CBAM module will be used by the attention module.

**1.4 Conclusion**

This study on sports risk assessments aids schools and colleges in determining risk factors and enhancing their sporting environments for the benefit of their kids' futures. In this study, a multi-scale one-dimensional convolutional neural network model for estimating sports risk is developed, and the model is further enhanced by residual networks and attention mechanisms.

**1.5 Contribution**

To get better performance results, the author experimented with the data set, as shown below.

**Comparison with other evaluation methods:** Bp-based, RBF-based and CNN-based and MSAR methods are compared. Among all the methods MSAR method has achieved the best performance with 95.2% precision and 93.1% F1 score.

**Multi-scale features vs single scale features:** multi-scale features yielded the greatest results.

**Experimental results of attention:** The attention mechanism produced the highest performance results by enabling the network to extract more discriminative characteristics.

**Experimental Results of Dropout:** The dropout technique yields the best outcomes.

**SECTION 2: CRITICAL ANALYSIS**

**2.1 Overall Assessment**

The author's detailed explanations made the material easy to read. In addition, the author did a great job of keeping a pleasant flow while offering different approaches of neural networks. The paper's primary merit is its experimentation of data with different methods with the underlying algebra, and outcome analysis. I must commend writers' writing abilities.

**2.2 Research methodology**

**Convolutional neural Network**: It uses a feed-forward multilayer neural network model. Convolutional and pooling layers of the network in this case are used for feature learning. Feature maps are combined with a SoftMax function layer and sent to subsequent layers using fully linked layers to provide classification results.

**Multi-scale ID convolutional Neural Network:** The convolutional layer, activation layer, and pooling layer of CNN process the input data. A multi-scale fusion architecture is constructed utilizing convolution kernels of varying sizes to actualize the complementarity of information at several scales. The initial part of the network model structure is used to extract short-term information from the original vibration analysis.

**Residual Network:** Training will be challenging, and training accuracy will decline as neural network layers are added. The residual neural network will address this problem by stacking several residual modules that provide the identity mapping for the network layer via a shortcut link. Instead of a straight map that stacks several network layers, the residual module fits a residual map. The direct mapping can be redefined as H(x)=F(x)+x where X is assumed as input module.

**2.3 New Knowledge Learned**

I have learned different models like convolutional neural networks, Residual Networks, Multiscale attention residual network model.

**2.4 Future Research**

The convolutional neural network needs a large amount of data for good performance other wise it would run into overfitting problem. In future researchers needs to focus to reduce overfitting of convolutional neural network model and, we need to improve the model to estimate accurate weights of the feature even with reasonably small amount of data.

**Section 3: Question to discussed**

Does the accuracy is enough for the proposed model, what are possible reasons that reduced accuracy.