Article

# Analysis of the kinematics of punches in karate and their recognition using an artificial neural network

**Ilshat Khasanshin [1], Andrey Labintsev [2] and Dmitry Balashov [3]**

[1] Financial University under the Government of the Russian Federation; iykhasanshin@fa.ru
[2] Financial University under the Government of the Russian Federation; ailabintsev@fa.ru
[3] Financial University under the Government of the Russian Federation; dabalashov@fa.ru

**Abstract:** (1) Background: place the question addressed in a broad context and highlight the purpose of the study; (2) Methods: describe briefly the main methods or treatments applied; (3) Results: summarize the article's main findings; (4) Conclusion: indicate the main conclusions or interpretations. The abstract should be an objective representation of the article, it must not contain results which are not presented and substantiated in the main text and should not exaggerate the main conclusions.

**Keywords:** punch; classification; sensors; neural networks (List three to ten pertinent keywords specific to the article; yet reasonably common within the subject discipline.)

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## 1. Introduction

Karate is a traditional Japanese martial art. However, this Japanese martial art has gained popularity all over the world. Sports competitions of national and world level are held in karate. The popularity of karate as a sport is growing, and in this regard, the methods of training karate athletes are increasingly becoming scientific in nature.

To develop effective training techniques, trainers need to understand the kinematics and dynamics of karate punches. Therefore, our research was aimed to analyze the velocity fields of punches in karate, as well as to develop and analyze various models of artificial neural networks for recognizing punches.

To solve the problems of the study, inertial measurement units (IMUs) were used, which included an accelerometer and a gyroscope. IMUs were attached to the wrists of karate athletes. The use of IMUs was due to the fact that in sports and martial arts, they proved to be an effective tool for analyzing the kinematics and biomechanics of human movements [1,2].

In [3], studies of the acceleration and speed of punches were carried out using IMUS that were installed on the wrists of boxers. The accelerometers in this study had a large range – 200g (g is the acceleration of gravity = 9.8 m / s2), but the acceleration graphs show that the maximum acceleration was about 25g. In addition, this acceleration corresponded to the final phase of the punch, when the athlete's fist stopped abruptly and this led to a large negative acceleration. This allows us to conclude that for studies of the kinematics of punches in martial arts, it is possible to limit the measurement range to 16-25g. In [3], it was found that the speed of punches in male athletes was 8.1±1.4 m/s for jab-out punches, and 7.7 ± 1.5 m/s for cross-out punches. The women had the following results: 6.6 = 1.6 m / s (job-out), 5.7 = 1.5 m / s (cross-out).

The authors of the work [4] investigated the difference between the biomechanics of punches of elite and novice boxers based on IMUs, which in the amount of 17 pieces were installed on the body of boxers. IMUs had an accelerometer measurement limit of 18g, they included an accelerometer, gyroscope, magnetometer. Since the IMUs were installed on each body segment, the contribution of the body segments to the punching technique of boxers was determined. In both groups (elite and novice athletes), the

elbow contributed the most to the cross-out technique, and the shoulder contributed the most to the hook and uppercut.
In [5], the analysis of the kinematics of boxers ′ punches using accelerometers was carried out in conjunction with videography. The authors [5] searched for the correlation of postures and fields of acceleration of blows with the fatigue of athletes. The graphs of punch accelerations given in [5] show that the maximum values are in the range of 20-40 m / s2, which also allows us to choose an IMU for experiments with a measurement limit of up to 16g. In [5], it is stated that a large number of degrees of freedom of human hands do not allow us to draw unambiguous conclusions about the kinematics of blows, so videography was additionally required. It can be noted that in this work, the magnetometer and gyroscope, which are usually included in the IMU, were not used, perhaps their use could lead to the fact that videography would not was needed.
Also, various techniques of artificial neural networks (ANN) are used to analyze the kinematics of punches in martial arts, which can also help in conditions of lack of data. The advantages of ANN have led to the fact that they are actively used in sports and martial arts [6]. For example, the authors [3] concluded that according to the accelerometer data, it is difficult to find the time when the boxer's hand begins to return after a punch. It can be assumed that the use of ANN methods can cope with this problem.
In [7], the ANN in the form of a multilayer perceptron was developed for the purpose of automating the data collection of boxers ′ punches. The input data for ANN was the IMU data that was attached to the boxers ′ wrist. The accuracy of punch recognition ranged from 87.2 ± 5.4 % to 95.33 ± 2.51%.
In [8], six different deep machine learning models for recognizing boxers ′ punches were investigated. The IMUs were installed in two versions: (1 – the IMUs was attached to both wrists; 2 – the IMUs was attached to both wrists and the third thoracic vertebra). The accuracy of the impact prediction was: for version 1 – 0.90 ± 0.12, for version 2-0.87 ± 0.09. For version 1, the support vector machine (SVM) model worked best (accuracy = 0.96), version 2 – the multi-layer perceptron neural network (MLP-NN) model (accuracy = 0.98).
Not much work is devoted to the analysis of punches in karate based on IMUs and ANN. And so far, no research has been conducted on a specific karate punch, which is called uraken in Japanese (a punch is made from the inside out).

## 2. Materials and Methods

### *2.1. Participants*

The study involved sixteen healthy participants (n=16), 12 men, 4 women, aged 22±3 years, weighing = 70±14 kg, height = 165±21 cm with 3-7 years of experience in karate. Ethical approval was granted by the Human Research 76 Ethics Commitee at Financial University under the Government of the Russian Federation.

### *2.2. Materials*

The design of the experiment can be seen in Figure 1.

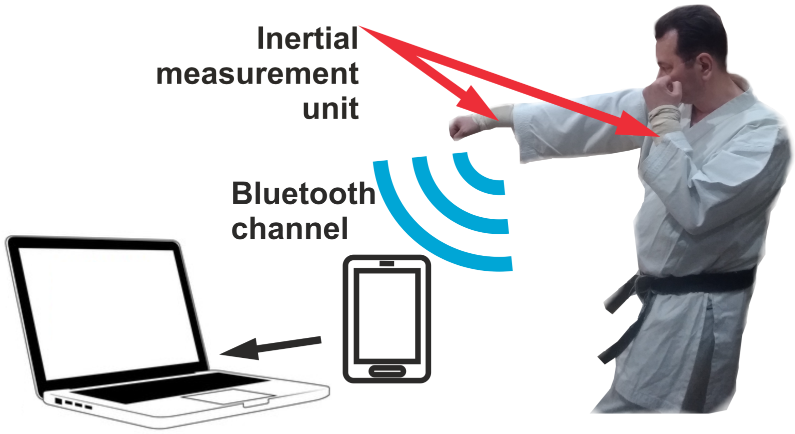


**Figure 1.** Design of the experiment

On the wrists of the athletes were fixed devices, which included a microcontroller, IMUs, and Bluetooth modules. Athletes punched in shadow fight mode. The IMUs (accelerometer and gyroscope) data was initially transmitted via the Bluetooth channel to the android device. On the android device, the data was saved as files for each type of punch. This data was then processed on the computer. In order to label and identify each punch for develop models of the artificial network, video recordings of the experiments were made. The data acquisition device (Figure 2) was a 50x20x10 mm box containing three modules – the microcontroller stm32f103 [9], IMU MPU9250 [10], and Bluetooth module HC-05 with a BC417143 chip [*].

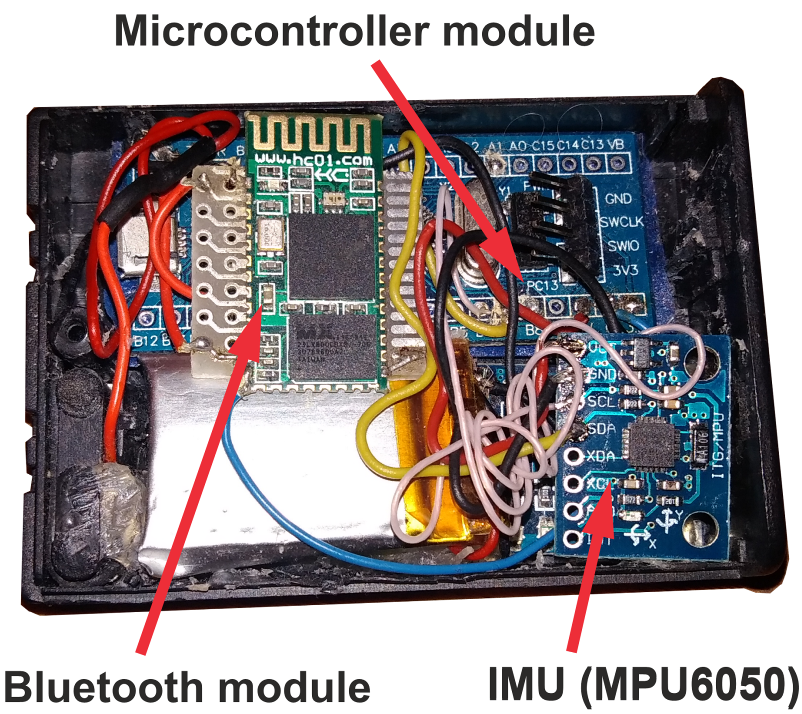


**Figure 2.** Data acquisition device

Figure 3 shows that the IMU device was attached to the athlete's wrist with boxing bandages. Figure 3 also shows the directions of the acceleration axes and the angular velocity of the gyroscope.

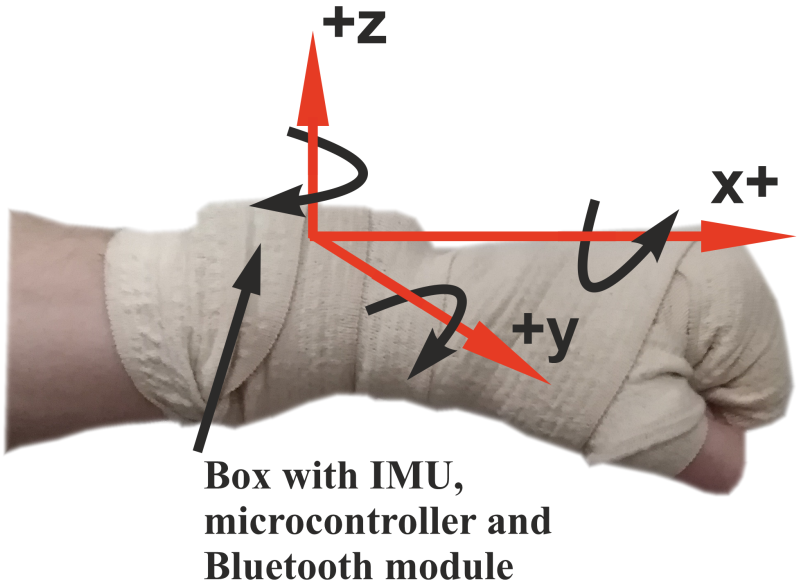


**Figure 3.** Measuring module attached to the arm with a boxing hand wrap

We don't use magnitometer measurements and don't calculate angles and position of sensor. We use only linear acceleration and gyroscope measurements.

To record session we use Xiaomi Redmi 7 camera with 1980x1080 resolution 30 fps. Video analysis was used to labeling ground truth punches. To record data we use Bluetooth Serial Terminal Android application.

Data collection session consist of the participant performing 1912 punches in shadow fight mode

Class of punches are:

1. Yun Tsuki (YT);
2. Mawashi Tsuki (MT);
3. Age Tsuki (AT);
4. Uraken (U);
5. No Punch (NP).

In Figures 4-7, the red arrow shows the approximate trajectories of the punches

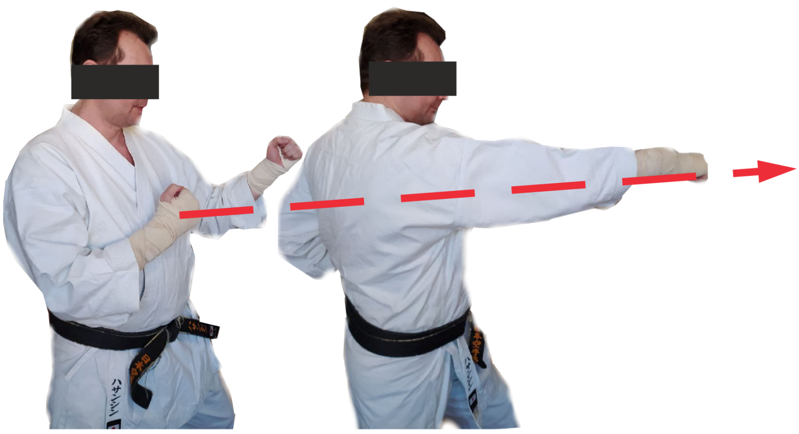

**Figure 4.** Yun Tsuki (YT)

**Figure 5.** Mawashi Tsuki (MT)

**Figure 6.** Age Tsuki (AT)

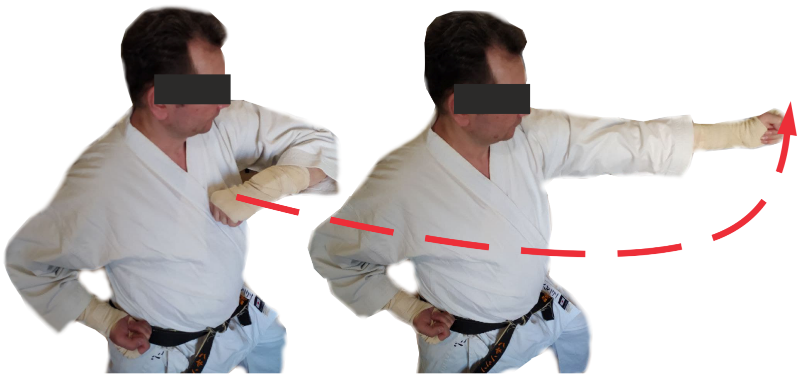

**Figure 7.** Uraken (U

### *2.3. Methods*

Measured data was packed to dataset X: every sample has 3 columns (x, y, z acceleration).

Train / validation random splitting was made with 10:1 propotional for each class. Histogram of classes samples distribution on the Figure 8.

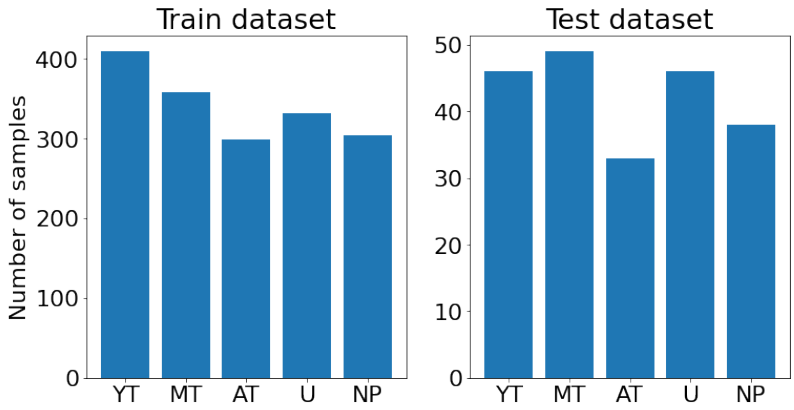


**Figure 8.** Train and test samples

Data preprocessing was conducted with python 3.7 packages: numpy, sklearn. Visualisation was made with matplotlib, Neural Net models build with tensorflow.keras 2.2. Raw data for different punch classes visualized on Figure 9.

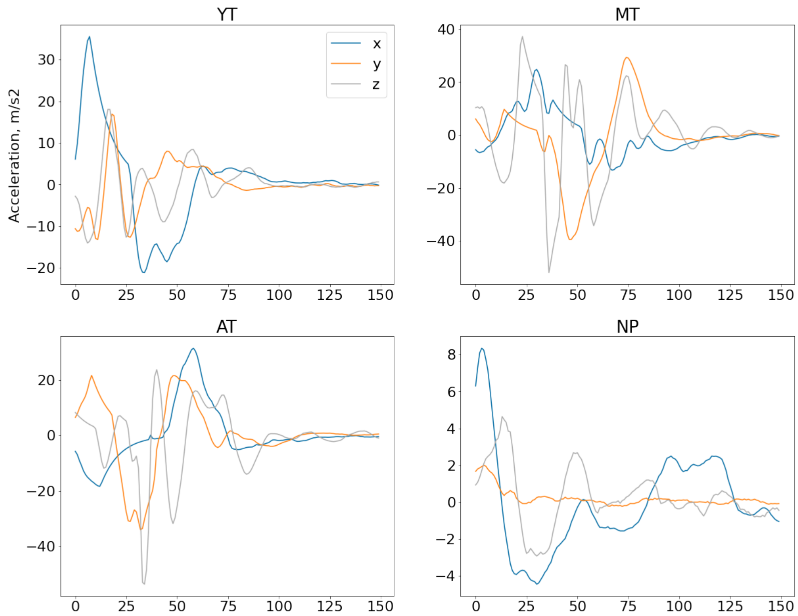


**Figure 9.** Measurement raw data for different punch classes

In experiments takes part 4 models:

1. multylayer perceptron;
2. 1 dimension convolution network from scratch;
3. 2 dimension convolution network with 2 layers;
4. 2 dimension convolution network with 3 layers.

Multiclass Accuracy used as a classification metric for all classes:

$$ACC = \frac{N_T}{N} \tag{1}$$

where $N_T$ - number of true classified punch, $N$ - total number of punches.
Precision, recall and F1-score were used as a classification metrics for single classes:

$$P = \frac{N_{TP}}{N_{TP} + N_{FP}} \tag{2}$$

$$R = \frac{N_{TP}}{N_{TP} + N_{FN}} \tag{3}$$

$$F1 = 2 \cdot \frac{P \cdot R}{P + R} \tag{4}$$

where $N_T P$ - number of true positive classified punch, $N_F P$ - number of false positive classified punches, $P$ - precision, $R$ - recall, $F1$ - F1 - score.
Models was trained using PC with Ubuntu 18.04 LTS, Intel(E) Core(TM) i7-6950x CPU, 64 GB RAM, GTX 1080ti 8 GB GPU. Total time about 4 hours.

## 3. Results

### *3.1. Simple multy layer perceptron*

Multy layer perceptron consist of 5 sequential layers with hidden size (450, 1024, 256, 128, 5), batch normalization, sigmoid and relu activations. After 100 epochs training we have 0.99 training and 0.87 validation accuracy. Classification metrics are on the Table 1.

**Table 1.** MLP classification metrics.

| Punch class | precision | recall | F1-score |
|---|---|---|---|
| YT | 0.87 | 0.93 | 0.91 |
| MT | 0.97 | 0.90 | 0.93 |
| AT | 0.83 | 0.90 | 0.87 |
| U | 0.92 | 0.96 | 0.94 |
| NP | 0.88 | 0.79 | 0.83 |

Confusion matrix is on Figure 10.

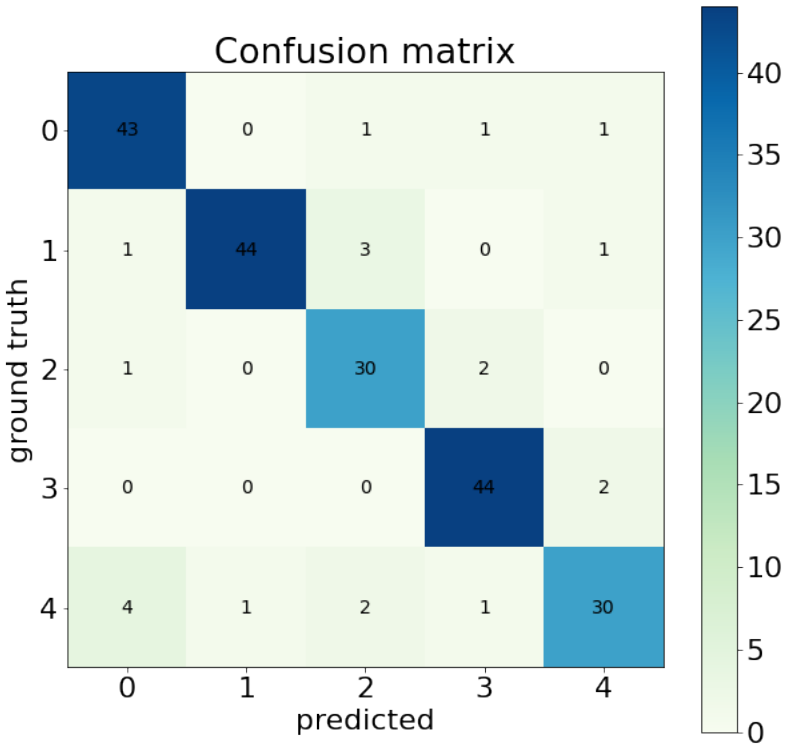


**Figure 10.** MLP confusion matrix

We see difference between train and validation accuracy, this means, that linear model is overfitting. To avoid this we try more complicated model - 1D convolution network.

### 3.2. 1D Convolution Network

1-dimension Convolution Network consist of 3 separate layers with 64 kernels each and relu activations. Optimizer is Adam, learning rate = 2e-3 and batch size 64. After 100 epochs training we have 0.81 training and 0.62 validation accuracy. Confusion matrix is on Figure 11. Classification metrics are on the Table 2.

**Table 2.** 1D CNN classification metrics

| Punch class | precision | recall | F1-score |
|---|---|---|---|
| YT | 0.64 | 0.85 | 0.73 |
| MT | 0.91 | 0.63 | 0.75 |
| AT | 0.86 | 0.75 | 0.81 |
| U | 0.85 | 0.98 | 0.91 |
| NP | 0.86 | 0.79 | 0.82 |

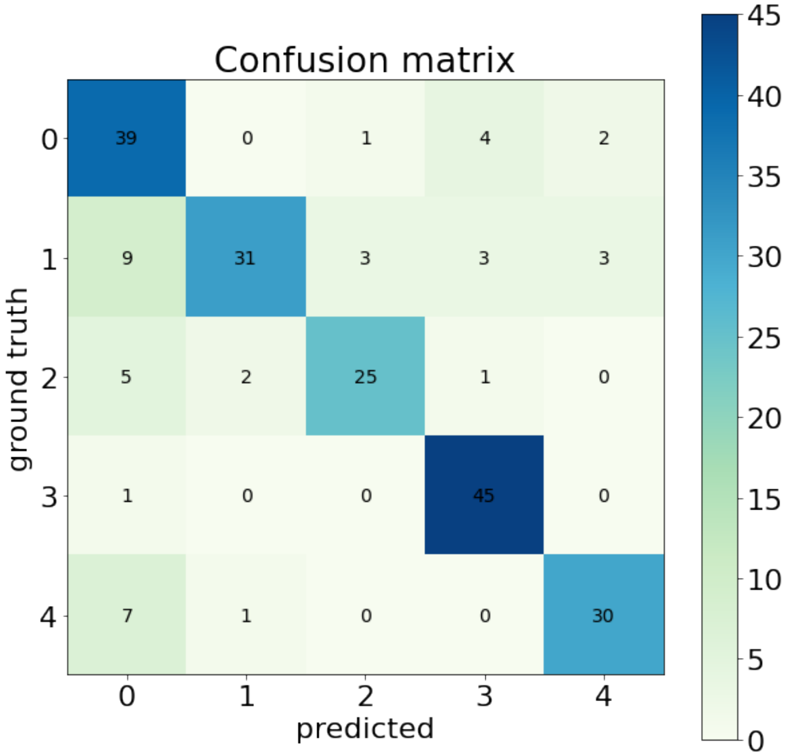


**Figure 11.** 1D CNN confusion matrix

138 During training process we observe small train accuracy, unstable validation accuracy and big loss. This means, that 1D convolution model is unsuitable for punch classification. So, we try to use feature combination and model with 2D convolution layers.

### 3.3. 2D Convolution Network

2-dimension Convolution Network consist of 2 layers, that inputs are both x,y and y,z axis. Layers has 72 and 88 kernels, size (2, 52), batch normalization and relu activations. Optimizer is Adam, learning rate = 2e-3 and batch size 64. After 100 epochs training we have 0.97 training and 0.93 validation accuracy. Confusion matrix is on the Figure 12. Classification metrics are on the Table 3.

**Table 3.** 2D CNN classification metrics.

| Punch class | precision | recall | F1-score |
|---|---|---|---|
| YT | 0.81 | 1.00 | 0.89 |
| MT | 1.00 | 0.94 | 0.97 |
| AT | 0.90 | 0.85 | 0.88 |
| U | 0.96 | 0.98 | 0.97 |
| NP | 1.00 | 0.81 | 0.90 |

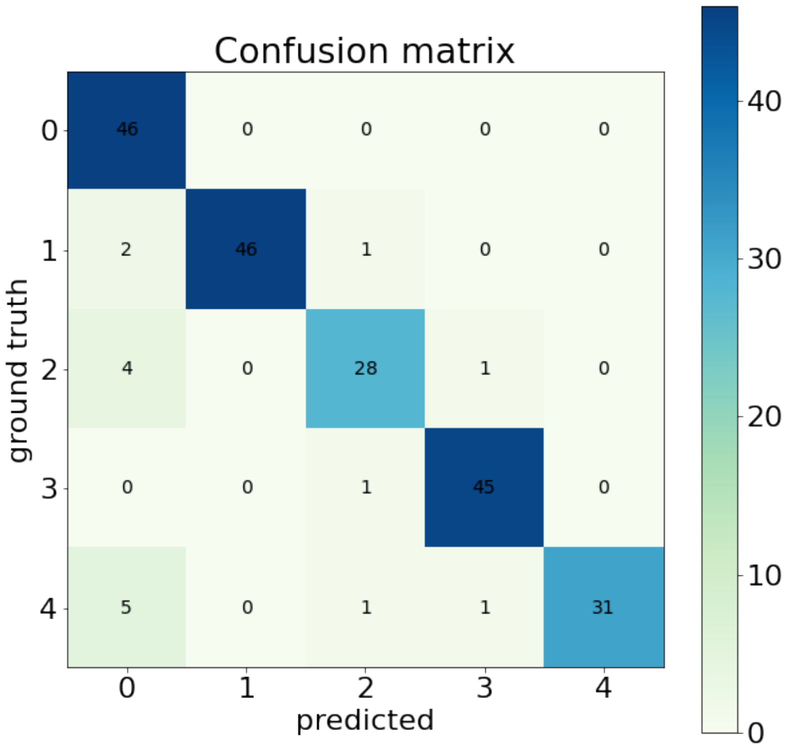


**Figure 12.** 2D CNN confusion matrix

We see much better train and validation accuracy, so we try deeper model with 3 2D convolution layers.

### *3.4. 2D Convolution Network with 3 layers*

2-dimension Convolution Network consist of 3 layers, that inputs are both x,y and y,z axis. First layer has 32 kernels with size (2, 32), other layers has 64, 64 and 96 (2, 2) size kernels. Batch normalization and relu activations also used. Optimizer is Adam, learning rate = 2e-3 and batch size 64. After 100 epochs training we have 0.98 training and 0.96 validation accuracy. Confusion matrix is on the Figure 13. Classification metrics are on the Table 4.

**Table 4.** 2D 3 layer CNN classification metrics.

| Punch class | precision | recall | F1-score |
|---|---|---|---|
| YT | 0.94 | 1.00 | 0.97 |
| MT | 1.00 | 0.98 | 0.99 |
| AT | 0.97 | 0.94 | 0.95 |
| U | 0.96 | 1.00 | 0.98 |
| NP | 1.00 | 0.92 | 0.96 |

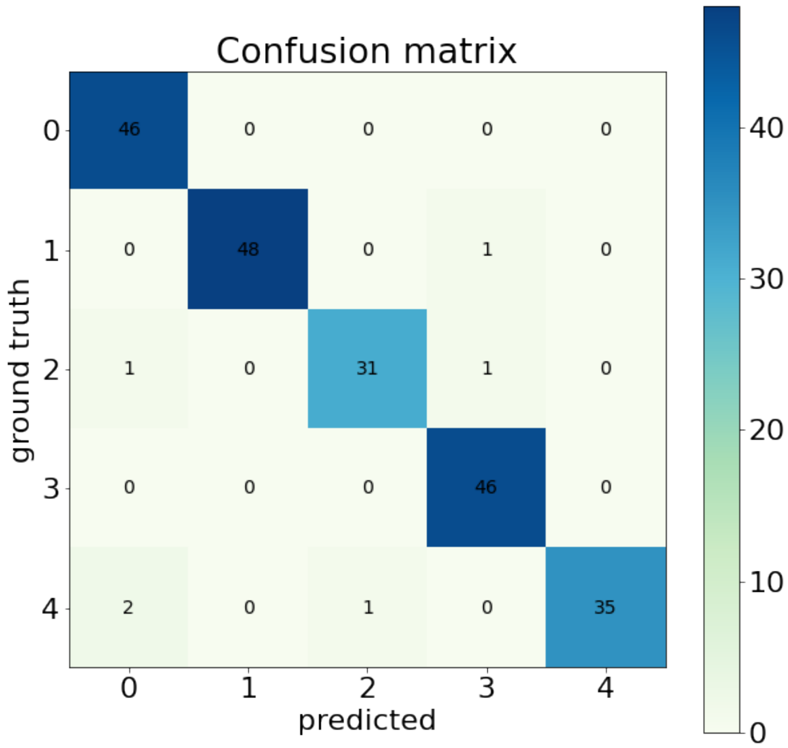


**Figure 13.** 2D 3 layer CNN confusion matrix

On training history we see much better train and validation accuracy, small loss. We try more layers, but this do not improve classification metrics

## 4. Discussion

Multilayer perceptron is a simple model and good baseline. Best F1 score is 0.95 for U-punch, worst is 0.86 for N-punch. Difference between train and validation accuracy is result of model overfiiting. Increasing number of training samples will solve this problem.
1D convolution model from [] work works very bad and not suitable for punch class prediction. Train accuracy is about 0.8, but validation accuracy only 0.65 and very unstable. Worst F1 score is 0.11 for MT-punch, best F1 is 0.81 for No-punch class. Loss after 100 epochs training is only about 0.3.
As we proposed, 2D convolution model with 2 conv layers works better. Metrics are like on mlp: best F1 is 0.93 for YT-punch and worst is 0.90 for U-punch class. A little gap between training and validation accuracy curves is tell about some overfitting, so we tested deeper conv model with 4 layers.
2D convolution model with 3 conv layer shows best result: 0.97 validation accuracy. Best F1-score 0.99 for YT-punch class, worst 0.90 for AT-punch class.
Comparing with MLP, we achieved better classification metrics and shift invariant model, based on 2D convolution.

## 5. Conclusions

Comparing with classic ML prediction methods, neural nets have a little smaller F1-score, but higher accuracy.

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**Institutional Review Board Statement:** The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of Financial University under the Government of the Russian Federation.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

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**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| IMU | Inertial Measurement Unit |
| MLP | Multi-layer Perceptron |
| CNN | Convolution Neural Network |

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