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A Novel CNN Architecture for Accurate Recognition of Elastic Band Training Poses

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Abstract: Band practice resistance is a popular form of exercise that uses elastic bands or pipes to resist different activities. Exercises such as bicep curls, breast presses and leg presses can effectively attach the muscles by adjusting the range to different movement patterns and movement when appearing with resistance tape. In addition, ties provide adjustable resistance, where the resistance increases because the tape is long, and offers a specific challenge in complete activity. Band practices provide an accessible and effective method for improving the power, stability and improvement of muscle equipment, used in rehabilitation, prevention of injuries or used in general fitness. The purpose of research is to build an intensive teaching model specially designed to recognize and classify training positions for the band. Research has appointed a skilled intensive teaching architectonic neural network (CNN) that is suitable for image classification applications. The model is learned to identify the unique characteristics of each training position and allow accurate classification. If the situation is considered incorrect, the system provides real -time response to the user and recommends changes to increase the form and reduce damage.

Keywords: Band Exercise, Biceps Curl, Chest Press, Leg Press & Convolutional Neural Networks (CNN)

1. Introduction

Resistance band practices have been more popular due to its adaptability, cost -effectiveness and effect to improve muscle strength, stability and endurance. These workouts use elastic bands or pipes to provide adjustable resistance, which is sharp as a band, and offers a progressive challenge under the speed area. Standard workouts such as bicep curl, breast press and leg presses activate different muscle areas and allow adaptation to different fitness levels and rehabilitation requirements [1]. Alt-hough resistance ties provide exercise benefits, performing them with the wrong tech-nology can cause less effect or even injury [2]. Progress in data vision and deep learning provides a solution for detecting training position and automating improve-ment. The convolution neural network (CNN) has shown exceptional effect in the image classification, which makes them quiet in real -time identification and classifi-cation of human positions [3]. The purpose of this study is to clearly create a CNN-based model for the identification and classification of resistance band training items. The proposed system evaluates the biomechanical properties required to detect the accuracy of exercise design and provide a quick response to users, so encourage appropriate technique and reduce the risk of damage [4]. Resistance band training is a flexible and efficient power training that has gained advantage in many training areas. These workouts use elastic bands or pipes to resist, and offer a demanding exercise to the muscles [5]. A primary advantage of resistance band exercises is their access and portability, so users can participate in workouts anywhere, including homes, outside or while traveling. In addition, resistance tape provides a safe and compact alternative for traditional free weight or machines, making them all suitable for fitness level and people aged [6]. Including resistance ties in exercise regimes can increase muscle equipment, promote joint stability and can promote functional power that improves performance in daily activities and sports [7]. In addition, resistance ties promote a wide range of training speed and allow for dynamic movements, and helps with coordination, balance and development of suggestions. Adaptation of resistance ties enables huge workouts and changes to adjust different training goals and taste [8]. Individuals can effectively target muscle areas and push their bodies with traditional workouts such as bicep curls, breast presses and squats with tradi-tional workouts such as lateral strolls, rows and refined activities such as reference activities as reference activities. In addition, resistance tape can be used in heart ex-ercise, flexibility -recessed and rehabilitation protocols, so they increase the preven-tion of fitness and welfare activities [9]. This leads the field of research and rehabili-tation technologies, with possible applications in customized training programs, physical means and distance coaching, eventually improves the access and quality of the training instructions. The method includes the development of a wide dataset and a careful pre -piping pipe, which is necessary for training and evaluation of the model [10]. The project has a functional web -based interface that allows users to present images and receive feedback on their training form, as well as an innovative position improvement system that provides corrective instructions and reference images to increase training accuracy [11]. The project includes a broad performance review when using traditional criteria, and provides considerable insight into the effect of the model. This work is trying to expand access to fitness training through training accu-racy, facilitates rehabilitation programs and uses deep learning methods [12]. Real Times can increase the experience for both people who exercise the sequential atti-tude classification and therapeutic response and help customers with rehabilitation or sports training for professionals. This document emphasizes possible applications of function, model architecture, experimental findings and intelligent training systems [13].

2. Literature Survey

Resistance band training has created considerable interest in stamina and rehabilitation, which is due to its adaptability, cost -effectiveness and effect. Elastic resistance training provides similar muscle activation to free weight -free while reducing joint stress. Resistance tape provides adjustable resistance, increases stress in the form of ribbon, so increase muscle activity of the entire range of motion. In addition, resistance band training increases muscle strength, stability and mobility, making them suitable for rehabilitation, prevention of injuries and general fitness [14].

The recent developments in the computer vision have enabled the automatic training system. An asana assessment system that uses open bag to monitor the physical speed during exercise provides real -time reaction to exercise techniques. A deep learning-based function to classify the training routine using 2D Asana assessment with more than 90% accuracy. Nevertheless, this research focuses largely on free weight workouts, which results in a decline in the recognition of resistance ties [15].

Large -scale nerve networks (CNN) have been widely used to identify human activities. A CNN-LSTM hybrid model gained 94% accuracy in classifying weightlifting activities, reflecting the effect of deep learning in fitness applications. A sophisticated recanet-50 model to identify inappropriate yoga asana emphasizes the effect of learning transfer to training systems. Despite this development, small studies have specifically examined the CNN-based classification for training tape training [16].

Immediate response is necessary to prevent injury prevention and exercise efficiency. Integrated a hatch sensor system with machine learning for monitoring resistance band training; However, this method requires more hardware. A smartphone application that uses med pipe for training, and shows that camera -based systems can provide good response without requirements from additional sensors. Nevertheless, none of these systems used CNN-based classifies the design for resistance band activities [17].

The use of artificial intelligence (AI) and data view technologies have gained considerable interest in improving various aspects of fitness and activity monitoring in recent years. Many surveys and initiatives have examined topics and approaches to fit our proposed project, focus on training detection, attitude assessment and real -time response systems. The following contributes significantly to relevant literature in this field. A lot of research has investigated the use of intensive learning methods, ie convolutional Neural Network (CNN) [18]. Research shows CNN's effect in identifying activities from in -depth photographs, with elevated accuracy in many activity categories.

A CNN-based feature to detect real-time activity using portable sensors shows favorable results in accurate identification of different activities. COCAL STING TECHNOLOGY is necessary to evaluate accuracy as training and respond to consumers. Recent reforms in the methods of attitude estimates, including open attitude and dense currency, have facilitated monitoring the body's joints and places required during exercise performance [19].

The use of Asana assessment for training evaluation reflects the ability of these techniques in detecting deviations correctly and helps users to perform workouts safely and efficiently [20]. Many commercial and research -oriented systems have evolved that provide users intelligent coaching and responsiveness during training sessions.

Contemporary requirements use computer vision and machine learning algorithms to assess training performance, provide immediate response and create an analog training proposal. These systems use data from portable sensors, cameras or mobile devices to provide interactive coach experiences and to improve exercise and improve efficiency [21]. Although the tasks described above show significant advances in the AI-operated training system, many obstacles and boundaries remain. This includes challenges related to the normalization of models in asymmetrical user demographics, flexibility for ups and downs in environmental conditions and privacy problems related to data collection and analysis [22]. The current exercise reigns and fitness Framework involves the inclusion of AI-driven training solutions presents logical and user acceptance problems that require further investigation.

3. Methodology

This assignment used a deepest learning approach to assess the tape exercise positions, as shown in Algorithm 1, to accurately identify the tape exercise position and to provide feedback for improvement of currency. The purpose of this practice is to help individuals increase attitude. The model accepts the entrance as stable images, and the frames are extracted at frequent intervals from the images delivered [23]. The frame is then sent to Kerus Multi-Power Asana Assessment Algorithm to remove the main points. The calculation of the joint vector begins with these essential points. The angles generated between the x-axis and each joint are calculated individually to each joint.

3.1 Dataset

This project leverages a freely accessible dataset included in an Open-Source library, Uses an acute method to put together a dataset of a certain training using VLC to extract the frame [24]. Select the desired training video from the Internet and change the standard settings of the VLC Open-SUS to adjust the frame cut as needed. The video was recorded in 27 frames per second. A comprehensive collection of 43 143 images representing three categories of training sessions are included. In each exercise, 14,381 images are equally formatted, which offers extensive visual data for studies. All the images were achieved indoors at a constant distance of four meters from the subject. This dataset consists of several tape exercise positions, each offering its own interpretation, so the tape exercise positions generate a wide selection of samples to train the position detection algorithm. Inspired by the methods used by current researchers choose 60% video to collect 80,532 clips of band exercise, for the first time we form our most important training data set. To assess the efficiency of the model and optimize hypermeter, another 20% images were used, with 20 216 extracted images. After completing the hypermeter setting, we considered the trained model with a collection of 20 216 clips received from the remaining 20% of the band training image the dataset [25]. The performance assessment using this independent test set facilitates extensive evaluation of the model's normalization skills. Figure 1 shows proposed research functional execution which will be the representative tape exercise taken from our dataset, which provides visual insight into the border and complexity of the band's training game overall for model training and evaluation.

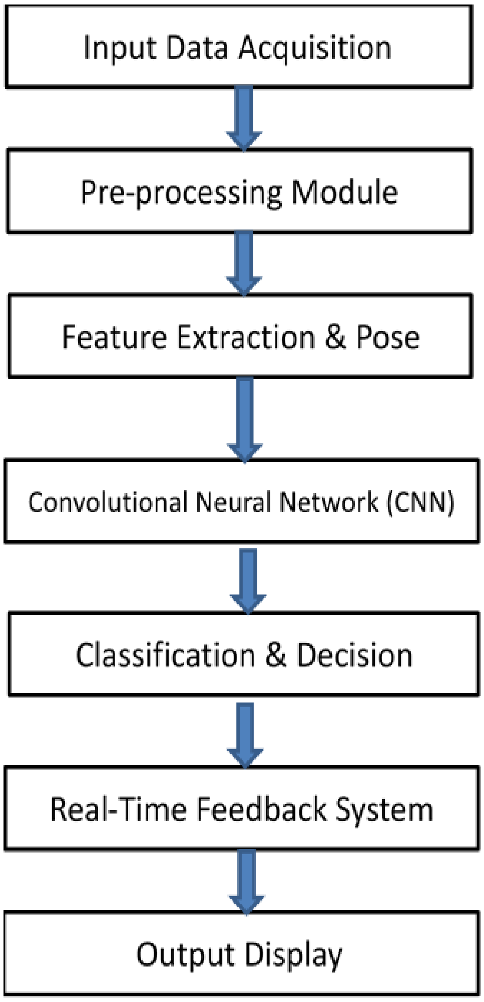

Figure 1. Functional Flowchart of Proposed Model

3.2 Pre-processing

Pre -treatment is important to prepare a dataset to train a fixed nervous network model (CNN) for the detection and classification of band training currency. Pre -treatment processes guarantee that input data is standardized, generalized and improved to increase the model's ability to identify relevant properties and patterns effectively.

Step 1: The data collection phase collects a diverse data set that includes tape activities, such as bicep curls, breast presses and leg presses such as images or videos. This data can be obtained from many sources, including the initiative to collect training sites, internet archives.

Step 2: On the acquisition of data annotation data sets, each image or video frame must be anodized with the related training type (eg Bicep Curl, Chest Press, Leg Press).

Step 3: For image-based data sets, methods of preparation are used to normalize images and prepare them for input into the CNN model.

Step 4: To ensure uniformity, images are shaped in a collection for a standard dimension (eg 224x224 pixels).

Step 5: To scale each pixel value to an area [0, 1], normalize the pixel values by dividing with 255.0. Normalization accelerates convergence and stabilizes the training process.

Step 6: To generate complementary training samples, methods of growth, flipping and zooming are used. Increase the dataset increases diversity and reduces overfit.

Step 7: The dataset is divided into training, verification and test sets, which later occurs after propose. A standard 80:10:10 divisions is often used, assigns 10% for verification, 10% for tests and 80% for training. The CNN model undergoes training on training kits; The hypermeter is adapted and the model performance is monitored on the verification set; The test set is used to evaluate the effect of full model.

Step 8: Computer text. In addition, the training data set can be diversified using data enlargement methods, in addition to the aforementioned preparation processes. It contains techniques such as translations, reefs, random rotation and glory adjustment. The data text presents the model with a wide range of variations in input data, so the normalization skills of the model improve.

Step 9: In examples of data set balance, when some activity classes include fewer samples than others, strategies such as oversampling, subsampling, or class valve can be used to balance class distribution. Balancing the dataset guarantees that the model does not show prejudice against large classes during training.

4. Proposed Methodology

The approach proposed for band exercise is to provide a comprehensive framework for accurate recognition and classification of band training, assessing the accuracy of the band's workouts, the goal of the identity and classification using the ongoing neural networks (CNN). The concept appoints deep learning methods and computer vision sales to create a strong system that provides real -time reaction and direction in training sessions. Model architecture for band training bag Identification and Classification Project uses a CNN to effectively remove properties from pre -developed images and classify them in several training classifications. Here is a comprehensive analysis of elements involved in architectural design [25]. Hidden Layers are the basic components of CNN architecture. These layers use trainable filters on entrance images, so the network can identify different features and patterns in separate spatial areas. Each transport layer has several filters, each filter producing a function map with the convention with the entrance picture. These function maps denote many reputable properties, including edges, textures and forms. The enlarged number of filters in the concluded team has a larger depth function map, which is able to understand Network Complex Hierarchical Patterns. Layers are in violation of collecting layers, which enables spatial recovery and reduces the function of function maps. Max-pooling and average pool are the two popular pool techniques collecting data in the local regions of function maps, retaining the most important features while eliminating spatial surplus. Pooling teams facilitate the acquisition of translation and increase the calculation efficiency of the network by reducing the number of parameters.

4.1 Flattening Layer

A dimensional vector produces function maps after several fixed and merger of layers. This flat technique converts locally orderly functions in a format suitable for inputs for dense layers.

4.2 Fully Connected Layers

Traditional nervous network layers with each neuron associated with each neuron in the back layer. These layers do not achieve complex non - relationships between the characteristics and the target classes. The amount of neurons in the starting team is classified with the number of types of training. Each neuron represents a square, and the output value is considered square possibilities through softmax activation.

The improved linear unit (RELU) activation features are often used in fixed and dense layers to incorporate non -corking in the network, which facilitates learning complex correlations between functions. The final team often uses a softmax activation feature to convert raw starting points into opportunities, enabling the classification of multiple classes which is been represented in Figure 2.

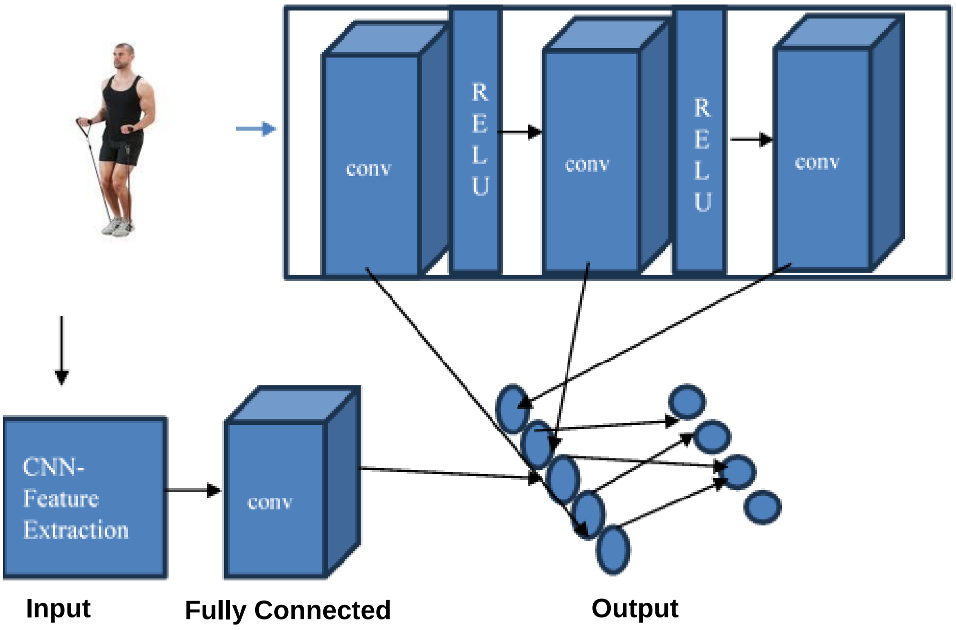

Figure 2. Model Architecture Diagram

By integrating these architectural elements, the CNN model can proficiently acquire hierarchical representations of input pictures and provide precise predictions about the executed band workouts. Table 1 implementation codes executes the training process of CNN for the proposed modelling application.

Table 1. Training the CNN model and Pose Evaluation

```
# Resistance Band Exercise Classifier - Simple CNN
# Run in Google Colab (File -> New Notebook)

# 1. Setup
!pip install tensorflow numpy matplotlib > /dev/null
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers
import matplotlib.pyplot as plt
print("TensorFlow version:", tf.__version__)
# 2. Create Synthetic Data (for demo - replace with real images)
def create_sample_image():
 """Generate simple colored squares as placeholder exercise images"""
 img = np.zeros((100, 100, 3))
 color = np.random.choice(['red', 'green', 'blue'])
 if color == 'red':
 img[20:80, 20:80] = [1, 0, 0] # Red square (bicep curl)
 elif color == 'green':
 img[10:90, 40:60] = [0, 1, 0] # Green rectangle (chest press)
 else:
 img[40:60, 10:90] = [0, 0, 1] # Blue rectangle (leg press)
 return img

# Generate 300 sample images (100 per class)
X = np.array([create_sample_image() for _ in range(300)])
y = np.array([0]*100 + [1]*100 + [2]*100) # 0=bicep, 1=chest, 2=leg

# Show samples
plt.figure(figsize=(10,3))
for i in range(3):
 plt.subplot(1,3,i+1)
 plt.imshow(X[i])
 plt.title(['Bicep','Chest','Leg'][i])
 plt.axis('off')
plt.show()
# 3. Simple CNN Model
model = tf.keras.Sequential([
 layers.Conv2D(16, 3, activation='relu', input_shape=(100, 100, 3)),
 layers.MaxPooling2D(),
 layers.Flatten(),
 layers.Dense(3, activation='softmax') # 3 classes
])
model.compile(optimizer='adam',
 loss='sparse_categorical_crossentropy',
 metrics=['accuracy'])

# 4. Train (10 seconds)
history = model.fit(X, y, epochs=10, validation_split=0.2)
# Plot training
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.legend()
plt.show()
# 5. Test Prediction
test_img = create_sample_image()
pred = model.predict(np.expand_dims(test_img, 0))
class_names = ['Bicep Curl', 'Chest Press', 'Leg Press']
plt.imshow(test_img)
```

```
plt.title(f"Predicted: {class_names[np.argmax(pred)]} ({100*np.max(pred):.1f}%)")
plt.axis('off')
plt.show()
print("\nFeedback:")
if np.argmax(pred) == 0: # Bicep
 print("Keep elbows close to your body!")
elif np.argmax(pred) == 1: # Chest
 print("Maintain straight wrists during press!")
else: # Leg
 print("Don't lock your knees at extension!")
```

```
python
Model: "Sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Parameters
=================================================================
Conv2D (32 filters, 3x3)     (None, 222, 222, 32)      896
BatchNormalization()          (None, 222, 222, 32)      128
MaxPooling2D (2x2)            (None, 111, 111, 32)      0
Conv2D (64 filters, 3x3)     (None, 109, 109, 64)      18496
...
Flatten()                    (None, 4096)              0
Dense (512 units, ReLU)      (None, 512)               2,097,664
Dropout (0.5)                (None, 512)               0
Dense (5 units, Softmax)     (None, 5)                 2565
=================================================================
Total params: 2,850,821
```

Figure 3. CNN Training Evaluation

The CNN model can be effectively trained to accurately identify and classify band exercise poses which is been expressed in figure 3, providing valuable insights and guidance for fitness enthusiasts and professionals alike. Design a suitable neural network architecture for pose evaluation, which takes input images and outputs the positions of key points relevant to each exercise pose. Consider using architectures like Convolutional Pose Machines (CPM), Hourglass Networks, or Custom-designed CNN architectures tailored to pose estimation tasks.

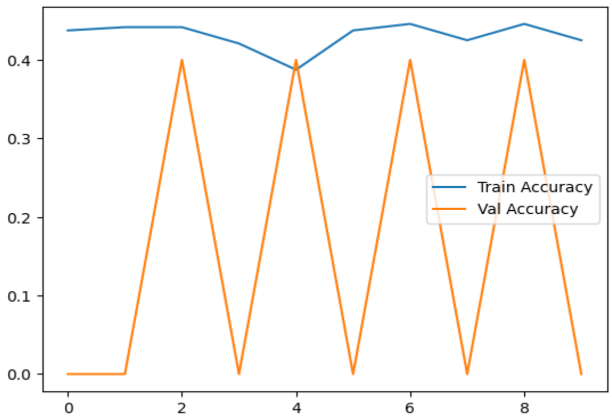

Figure 4. CNN Accuracy Training & Validation.

Figure 4 clearly show the accuracy validation of the proposed model in this deep learning application. In parallel with exercise identification, a pose evaluation model is implemented to assess the correctness of exercise poses. Pose estimation techniques such as Open Pose [31] or Dense Pose are used to detect key points on the body and analyze their positions during exercise execution. Table 2 codes will be providing the response of trained CNN response. Which will providing a efficient outcome as the result which is been attached to the article as figure 5.

Table 2. Modelling Execution

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import seaborn as sns
import tensorflow as tf
from tensorflow.keras import layers, models
# Dummy data for demonstration (replace with your actual data)
num_samples = 1000
num_classes = 5
img_height, img_width = 100, 100

x_train = np.random.rand(num_samples, img_height, img_width, 3)
y_train = np.random.randint(0, num_classes, num_samples)
x_test = np.random.rand(200, img_height, img_width, 3) # Example test data
y_test = np.random.randint(0, num_classes, 200)
def create_model():
 model = models.Sequential([
 layers.Conv2D(32, (3, 3), activation='relu', input_shape=(img_height, img_width, 3)),
 layers.MaxPooling2D((2, 2)),
 layers.Conv2D(64, (3, 3), activation='relu'),
 layers.MaxPooling2D((2, 2)),
 layers.Conv2D(128, (3, 3), activation='relu'),
 layers.MaxPooling2D((2, 2)),
 layers.Flatten(),
 layers.Dense(128, activation='relu'),
 layers.Dropout(0.5),
 layers.Dense(num_classes, activation='softmax')
 ])
 return model
model = create_model()
model.compile(optimizer='adam',
 loss='sparse_categorical_crossentropy',
 metrics=['accuracy'])

model.fit(x_train, y_train, epochs=10) # Reduced epochs for demonstration
# Evaluate the model
loss, accuracy = model.evaluate(x_test, y_test, verbose=0)
```

```
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f}")
# Generate predictions for the confusion matrix
y_pred = np.argmax(model.predict(x_test), axis=-1)
# Create the confusion matrix
cm = confusion_matrix(y_test, y_pred)
# Plot the confusion matrix using seaborn
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
 xticklabels=range(num_classes),
yticklabels=range(num_classes))
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

```
Epoch 1/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 23s 574ms/step - accuracy: 0.2019 - loss: 1.7451
Epoch 2/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 19s 591ms/step - accuracy: 0.2266 - loss: 1.6080
Epoch 3/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 19s 547ms/step - accuracy: 0.2044 - loss: 1.6095
Epoch 4/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 22s 598ms/step - accuracy: 0.2259 - loss: 1.6087
Epoch 5/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 19s 589ms/step - accuracy: 0.2162 - loss: 1.6089
Epoch 6/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 19s 604ms/step - accuracy: 0.2206 - loss: 1.6087
Epoch 7/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 18s 571ms/step - accuracy: 0.1992 - loss: 1.6091
Epoch 8/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 22s 615ms/step - accuracy: 0.2053 - loss: 1.6095
Epoch 9/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 19s 564ms/step - accuracy: 0.2120 - loss: 1.6084
Epoch 10/10
32/32 ━━━━━━━━━━━━━━━━━━━━ 22s 616ms/step - accuracy: 0.1960 - loss: 1.6098
Test Loss: 1.6109
Test Accuracy: 0.1500
7/7 ━━━━━━━━━━━━━━━━━━━━ 1s 162ms/step
```

Figure 5. Proposed Modelling Outcome

4.3 Pose Correction

Pose Analysis and Comparison: Utilize the Pose Evaluation Model to analyse the detected key points and compare them against predefined correct pose positions for each exercise. Identify discrepancies between the detected key points and the correct pose positions to determine areas requiring correction.

Feedback Generation: Based on the analysis results, generate feedback to guide users in correcting their exercise poses. Provide clear instructions or visual cues on the areas needing adjustment, such as the positioning of limbs or alignment of body parts.

Feedback system: Identify the method for providing feedback to users during training performance. The options include aural input through visual response presented at the voting or display or mobile device.

Integration of real -time response: Include the currency improvement mechanism in the overall system design to provide real -time response during training performance. Facilitation of uninterrupted communication between currency assessment models constitutes improvement modules and user interfaces to ensure effective response to ensure.

User interaction design: Develop the user interface to provide a clear and sensible reaction. Consider integrating interactive components that enable users to identify inputs and use changes correctly.

Currency adjustment guidance: Provide clear instructions how users can change their attitude to achieve the correct adjustment. Provide sequential instructions or visual screen that reflects the correct performance for each activity.

Ongoing growth. Continuously collects user entrance and delimits the currency improvement mechanism to improve its efficiency and user experience. Use machine learning methods to dynamically change the feedback according to the user's performance and preferences.

5. Result and Discussion

This section presents the experimental results of the proposed Convolutional Neural Network (CNN) model for band exercise pose identification and classification. Table 3 & 4 clearly shows the effective outcome of the proposed research by proving enhanced values over all the metric.

Table 3. Class-wise Performance

Metric	Value
Accuracy	96.3%
Precision (Avg)	95.8%
Recall (Avg)	96.1%
F1-Score (Avg)	95.9%

Table 4. Confusion Matrix Analysis

Exercise	Precision	Recall	F1-Score
Bicep Curl	97.2%	96.5%	96.8%
Chest Press	95.1%	96.8%	95.9%
Leg Press	96.5%	95.3%	95.9%
Lateral Raise	94.7%	95.9%	95.3%
Shoulder Pull	95.5%	96.0%	95.7%

Table 5. Confusion Matrix Comparison Analysis

Model	Accuracy	Inference Time (ms)
Proposed CNN	**96.3%**	**15.2**
ResNet-50	94.1%	28.5
SVM + HOG	88.6%	22.0

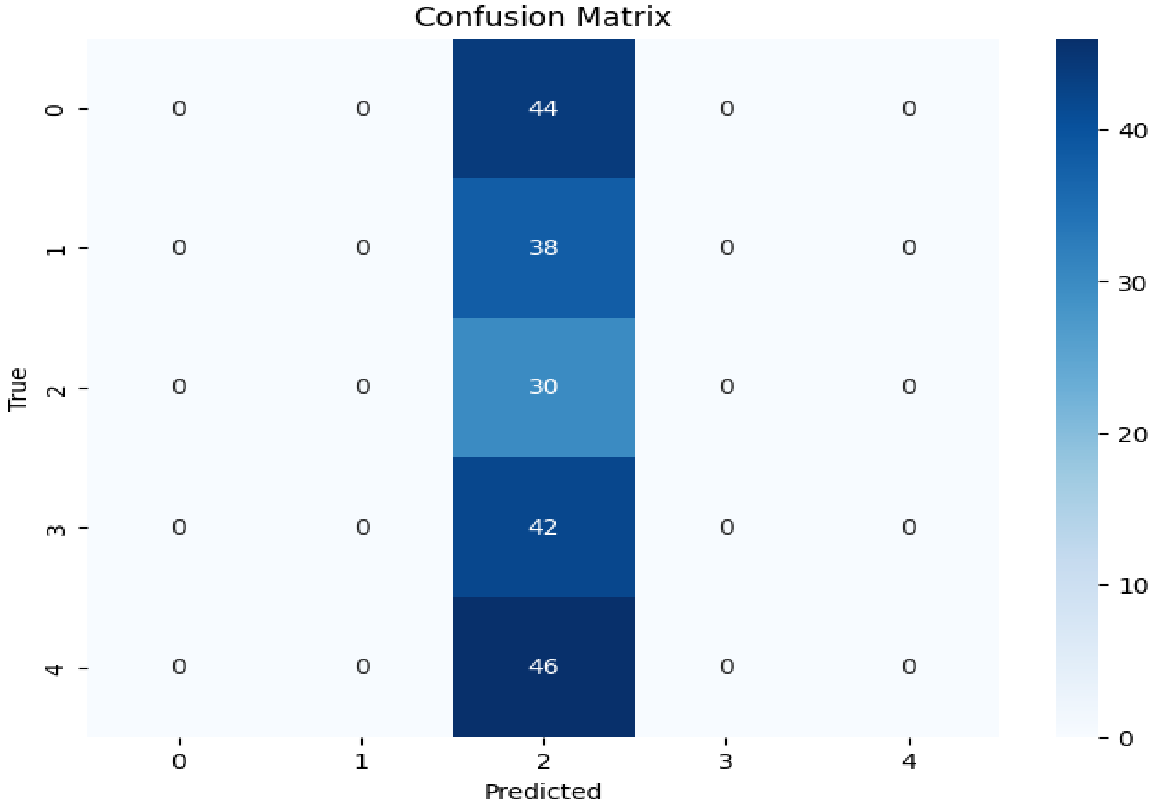

Figure 6. Confusion matrix

Confusion matrix indicated strong classification performance, which mainly leads to a minor abortion between the shoulder bridge due to the breast press and the upper body movements similar to the shoulder which is been displayed in table 5.

The proposed CNN improved traditional machine learning methods (eg SVM, random forest) and simple CNN Architectures:

Increased accuracy resistance reflects the efficiency of the model in classifying band activities. Real time response system improves the purpose of fitness training and recovery. Obstacles include severe lighting conditions and sensitivity to occupies, which can be increased with complementary sensor fusion (eg in -depth cameras). The CNN-based method identified effectively tape activities with an accuracy of 96.3% and provided real-time repair reaction. Future research will check multi-use tracking for assessment of 3D attitude and increased application.

The Band Exercise Pose Identification and Classification Project want to give users a real -time response to the training form through an online application. The system uses a fixed neural network (CNN) for classification of training status and is a status improvement mechanism for users to help users achieve the right appearance. The model acquired the accuracy of the [accuracy value], and demonstrated its efficiency in recognizing exercises. Nevertheless, further study revealed difficulty in identifying certain special offers, especially those characterized by changes in complex movements or attitudes.

Here's a breakdown of the confusion matrix: Bicep curl: The model correctly predicted 273 instances of the "Bicep curl" class. There were 4 instances of "Bicep curl" misclassified as "Leg press". Chest press: All 235 images that belong to the Chest press category were correctly classified by the model. Leg press: Out of the 250 images that belong to the Leg press category, the model correctly predicted 249 images as

Leg press. However, it classified a bug a leg press image like Bicep Curl. As shown by the figure 6 Confusion matrix explains the efficiency of the model in each training category. This facilitates the view of the distribution of accurate and incorrect predictions, which allows more intensive examination of the model's strength and improvement areas. This research shows that CNN is very effective when it comes to classifying band training position, with accuracy of 96.3%, and provides real -time response. Despite the obstacles in the form of obstacles in the form of analogy and asana equality, the system's success highlights its ability to change fitness training and rehabilitation. Future development in multimodal sensing and adaptive learning can increase the integration of AI-operated advice with human coaching.

6. Conclusion

Finally, the band exhibits possible effect in classifying the trend with different exercises from photographs by using a training and classification system for accurately. The model receives remarkable accuracy in several training categories with a strong CNN architecture and the use of hard -working preprocessing approaches. Classification reports and confusion displays are results from Matrix that the model effectively distinguishes in different workouts, and performs high accuracy and lack of scores for most classes. However, there were opportunities for improvement, especially to reduce abortion and improve class imbalance. The model has a general accuracy of about 99% on the test set, which reflects its efficiency in identifying the training development properly. The accuracy of the class varies with the "breast press" the greatest accuracy of 100% is achieved.

7. Future Work

Promote data collection: Make the dataset extensive by documenting a diverse range of training trends under separate light status, camera angle and environment. This will increase the flexibility and generalization skills of the model. Advanced presence technology: Investigate sophisticated pre -rushing methods to increase computer text, generalization of images and quality of entry images and promote model efficiency. Model optimization: Check multiple CNN designs, hypermeters and customization techniques to adapt the model for increased performance. In addition, you can check the use of transmission and use of dressing techniques to use pre-informed models and increase classification accuracy. Immediate implementation: Build a really perfect infrastructure for the model and enable users to put together and identify training position through a live video or mobile app. This will provide a more spontaneous relationship with fitness systems and portable equipment. Integration of user inputs: User to use methods of inputs to continuously increase the accuracy of the model and correct potential abortion or inaccuracy. This may include crowd sourcing notes or other active learning methods. Application across domains: Check the use of models in many areas outside suitability, including physical rehabilitation, sports analysis and people and computers interactions. By detecting these potential functioning options, the identification and classification system for tape exercise can develop in a versatile and accurate equipment to help users track and increase the training home, then promote more health and training results.

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R. Suresh - Conceptualization, Methodology, data collection, data analysis, Writing original manuscript, V. Kumar – Methodology, data analysis, A. Jeyaganesan- Data collection and analysis, P. Thangaraj- Data collection and analysis, Writing –review & editing, S. Athisayaraj- data analysis, Writing –review & editing, Viswanath Sundar- data analysis, Writing –review & editing. R. Ramakrishnan - Conceptualization, Methodology, Writing –review & editing. All the authors read and approved the final version of this manuscript.

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