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Comparative Analysis of CNN, RNN and LSTM for Synthetic Grip Strength Prediction

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***Abstract*— This study assesses the effectiveness of deep learning models, specifically Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM), in assessing synthetic grip strength data for stress ball and pencil grips. The aim is to determine the optimal model for grip strength classification and tackle issues such as temporal data and class imbalance. Synthetic data was created, preprocessed, and utilized to train the models on Google Colab employing TensorFlow and Keras. Hyperparameters, such as CNN kernel dimensions and RNN/LSTM sequence lengths, were refined. Performance was evaluated by accuracy, precision, F1 scores, and loss metrics. The RNN model surpassed both CNN and LSTM, with an accuracy of 94.99% and a precision of 0.56, particularly excelling in the classification of "Normal" grip strength instances. CNN and LSTM had difficulties with time dependencies and class imbalance, leading to reduced accuracy and increased loss. Although RNN has proven to be the most effective approach, subsequent research should concentrate on mitigating class imbalance and investigating hybrid models to improve performance.**

Keywords—Deep learning, Recurrent Neural Network (RNN), synthetic data, Grip Strength Analysis

I. INTRODUCTION

Crucially important for hand performance, grip strength is found in domains including ergonomics, fitness, and rehabilitation [1]. Often used to evaluate problems like frailty, recovery from traumas, and neuromuscular diseases [2], it acts as a surrogate for general muscular state. Conventional techniques of grip strength evaluation, such hand dynamometers, only measure fundamental force metrics, so offering little information on the dynamic features of grip performance, such endurance, accuracy, and temporal patterns [3]. This restriction makes it difficult for customized interventions and ergonomic solutions catered to particular requirements to grow.

This work investigates two different grip modes stress ball grip (object grasp) and pencil grip using synthetic data to replicate real-world sensor outputs to meet these problems. A scalable and reasonably priced substitute for real sensors, synthetic data creation allows fast model testing and development free from costly hardware [4]. This work analyzes time-series grip strength data using advanced deep learning techniques including Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory Networks (LSTMs), so revealing subtle variations in grip patterns and gender-specific differences. These revelations help to clarify the dynamics of grip strength, therefore opening the path for better individualized rehabilitation, exercise programs, ergonomic designs, and assistive technologies.

Deep learning models' application for grip strength analysis marks a major progress over conventional approaches. This study stresses dynamic analysis, therefore capturing the time evolution of grip strength, while earlier studies have concentrated on stationary data. Alias et al. [5] for example showed how well-advanced modelling techniques may be used in biomedical applications, therefore stressing the possibilities of data-driven approaches to get past the constraints of traditional hardware. Likewise, this work provides an affordable and scalable alternative by using synthetic data to solve the high expenses and impracticalities connected with extensive deployment of real sensors.

This study makes threefold contributions. First, it presents a fresh approach for synthetic data and deep learning model-based grip strength research, therefore enabling quick and affordable experimentation. Second, it offers a thorough evaluation of RNN, CNN, and LSTM models, concluding RNN to be the most successful for grip strength categorization. Third, it provides useful understanding of gender-specific grip patterns that can guide the creation of customized ergonomic equipment and rehabilitation programs. Unlike prior studies, this work emphasizes the use of synthetic grip strength data and evaluates deep learning models in a time-series classification context, aiming to bridge the gap between simulated and real-world sensor applications.

II. LITERATURE REVIEW

The development of advanced prosthetic hands has been significantly enhanced by recent advancements in machine learning, particularly through the use of deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These models have proven pivotal in improving sensory prediction, gesture recognition, and real-time responsiveness, making prosthetic devices more intuitive and closer to natural human

interactions is template has been tailored for output on the A4 paper size.

A. Deep Learning Models for Sensory Prediction and Gesture Recognition

Hybrid models, such as CNN-LSTM, have shown remarkable potential in predicting tactile sensations like temperature, hardness, and grip strength in prosthetic hands. For instance, Bai et al. [6] demonstrated that a CNN-LSTM model could accurately predict these sensations by leveraging the CNN's ability to extract spatial features and the LSTM's capacity to retain temporal information. This combination has proven effective for real-time sensory feedback, marking a significant advancement in prosthetic technology. Similarly, LSTM-based networks have been widely adopted for gesture recognition using Electromyography (EMG) signals. Studies by Jabbari et al. [7] and Samadani et al. [8] have highlighted the efficacy of LSTM networks in processing EMG data and classifying gestures, even in noisy signal environments and across diverse individuals.

B. Grip Strength and Endurance in Prosthetic Design

Grip strength and endurance are critical factors in prosthetic hand performance, influenced by both anatomical and physiological factors. Anatomical determinants, such as palm width and forearm size, have been shown to correlate strongly with maximal force production [9]. On the other hand, grip endurance is closely tied to muscle fiber composition, particularly the proportion of slow-twitch fibers, which are advantageous for sustained force production [10]. These insights have informed the development of more ergonomic and responsive prosthetic designs, ensuring greater comfort and functionality for users.

Recent studies have also explored the use of wearable sensors and smart gloves to measure grip strength and monitor rehabilitation progress. For example, Wang et al. [11] proposed a novel flexible sensor for grip strength estimation under different wrist angles, while Borik et al. [12] developed a smart glove to measure grip force in industrial settings. These innovations highlight the growing importance of sensor-based technologies in understanding and improving grip dynamics.

C. Gesture Recognition and Real-Time Performance

Gesture recognition is a cornerstone of prosthetic hand control, and RNN-LSTM models have emerged as a leading solution for improving real-time performance. Zhang et al. [13] demonstrated that an LSTM-based model using only four EMG channels could achieve high accuracy with low latency, making it suitable for real-world prosthetic applications. This emphasis on real-time performance is critical, as rapid and accurate gesture recognition is essential for effective prosthetic control.

However, data preprocessing remains a key challenge in EMG-based gesture recognition. Techniques such as signal rectification, moving average filters, and normalization have been widely adopted to reduce noise and extract relevant features [14]. These preprocessing methods significantly improve the accuracy of gesture recognition models, enabling more reliable and efficient control of prosthetic hands.

D. Synthetic Data and Cost-Effective Solution

The high cost and impracticality of physical sensors have led researchers to explore synthetic data as a viable alternative for model training and testing. Synthetic data generation allows for rapid experimentation and development without the need for expensive hardware, making it an economical solution for large-scale deployment [15]. This approach has been particularly useful in grip strength analysis, where synthetic data can simulate real-world sensor outputs and enable the development of robust deep learning models.

Recent developments have shown the growing relevance of computer vision and sensor fusion techniques in specialized applications. Shaharum *et al.* [16] utilized MediaPipe and OpenCV for real-time posture tracking, highlighting the role of vision-based tools in wellness and rehabilitation systems. In another application, Arafin *et al.* [17] leveraged YOLOv8 for improved dental image classification. Likewise, Faudzi *et al.* [18] applied image processing for thermal analysis in industrial diagnostics, demonstrating the adaptability of such techniques across domains.

While previous studies have explored the use of synthetic data for model training, few have specifically focused on grip strength classification using FSR-inspired simulations. This work contributes by proposing a structured, multi-class synthetic dataset and applying comparative evaluations across deep learning models, providing insights into their suitability for temporal biomedical signals.

III. Methodology

Generating synthetic grip strength data, preparing it, and testing three deep learning models Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network focus the approach of this work. The aim is to find the optimal model for general performance evaluation and synthetic data generating. As Fig. 1 shows, the procedure consists in five basic parts 1.

A. Overview

The study uses a software-based method to examine assessments of grip strength for pencil grips and stress balls. Real-world sensor outputs are simulated using synthetic data, which subsequently is utilized to train and assess CNN, LSTM, and RNN models. Using consistent performance criteria including accuracy, precision, F1 score, and loss proportions guarantees a fair comparison of the models. This method guarantees strong results and useful advice for grip strength study.

B. Data Generation

Synthetic data is created to imitate Force-Sensitive Resistor (FSR) readings for two grip types ("Pencil Grip" and "Stress Ball Grip") and two genders ("MAN" and "WOMAN"). The data set contains ten FSR measurements that represent pressure readings from nine hand locations (thumb to palm to index finger). Grip strength is divided into three levels: Weak (0), Normal (1), and Strong (2). A dataset of 50 users (25 males and 25 females) is generated, containing sensor readings and grip strength labels. Gaussian noise was added to simulate sensor variability, and user diversity was mimicked by randomly scaling FSR values within a biologically plausible range (±15%). Sampling was simulated at 50 Hz to reflect common FSR applications.

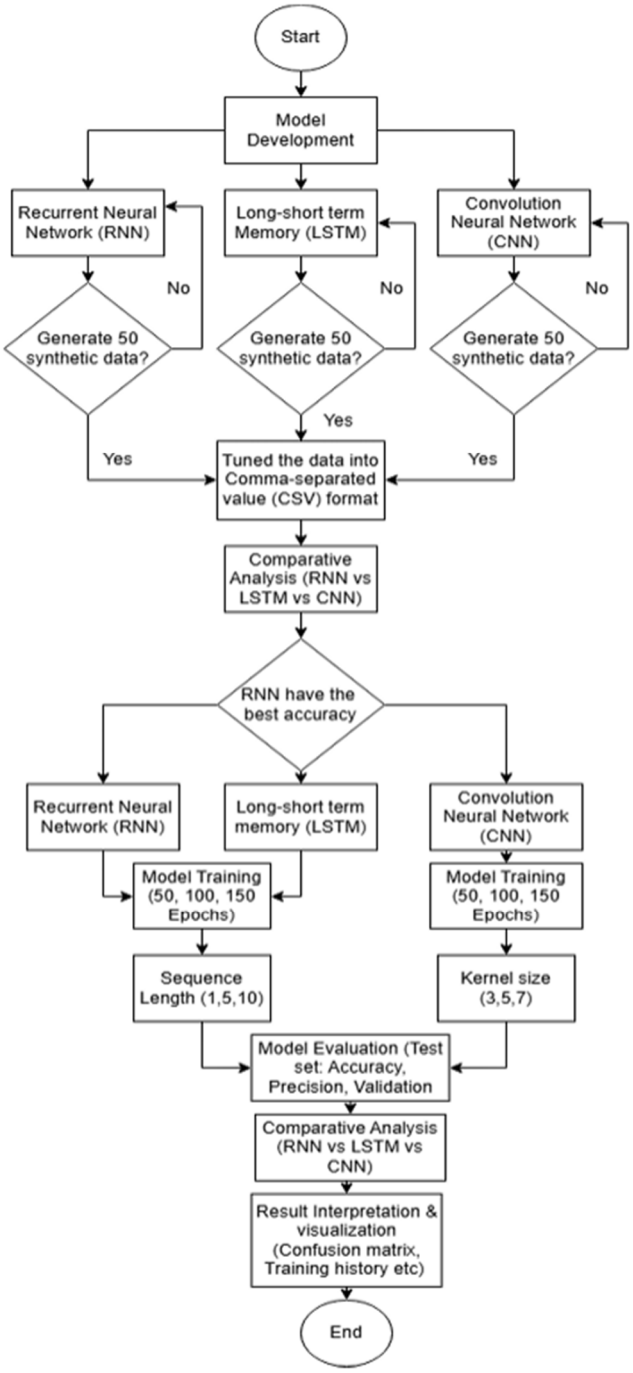


Fig. 1 System Flowchart

C. *Preprocessing and Saving Data*

The generated data undergoes preprocessing to ensure compatibility with the deep learning models. Sensor readings are normalized to a comparable range, and the dataset is saved in a CSV file for further analysis and modeling.

D. *Model Traning*

The preprocessed data is reshaped into a 3D tensor format to meet the input requirements of the RNN and LSTM models. The dataset is split into training (80%) and testing (20%) sets. The models are trained using TensorFlow and Keras, with 50 epochs and a batch size of 32. An early stopping mechanism is implemented to prevent overfitting. Early stopping was based on validation loss with a patience of 5 epochs, preventing overfitting and promoting model generalization.

E. *Model Evaluation and Visualization*

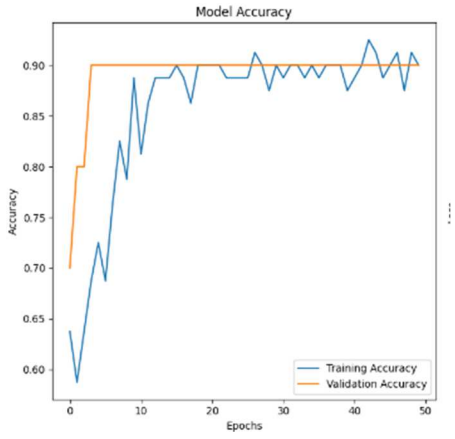
Model performance is evaluated using accuracy, precision, F1 score, and loss proportions. Training and validation accuracy are plotted over epochs to visualize the learning progress. The confusion matrix is used to assess classification performance, particularly for the "Normal" grip strength category. The results are presented as percentages, providing a clear comparison of the models' effectiveness in grip strength detection.

IV. Results and Discussions

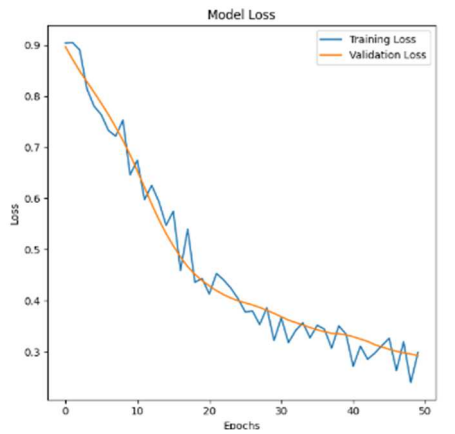
This section presents the results of the study, focusing on the performance of the Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) models in analyzing synthetic grip strength data. While the confusion matrix is a valuable tool for understanding class-specific performance, this section emphasizes accuracy, precision, F1 score, and loss metrics to provide a comprehensive evaluation of the models. These metrics offer a clear and concise comparison of the models' strengths and weaknesses, particularly in handling temporal data and addressing class imbalance. By excluding the confusion matrix, the discussion remains focused on the overall performance and practical implications of the models for grip strength analysis.

A. *Model Performance Comparison*

The RNN model achieved the highest performance, with a training accuracy of 90.00% and validation accuracy of 90.00%. It demonstrated strong generalization capabilities, with a training loss of 0.2884 and validation loss of 0.2531 (Fig. 2).



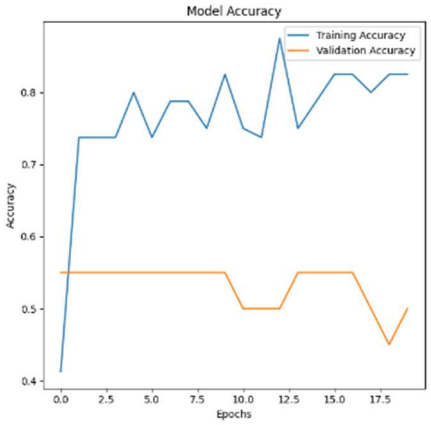
(a)



(b)

Fig. 2 RNN Model Performance. (a) Accuracy over epochs And (b) Loss over epochs

In comparison, the CNN model showed evidence of overfitting, with a very high training accuracy of 82.50% but a much lower validation accuracy of 50.00% (Fig. 3). This substantial disparity indicates that, while the CNN efficiently caught patterns within the training data, it struggled to generalize those patterns to previously unseen data, a common problem when models get overly complicated and memorize data rather than learning robust features. Meanwhile, the LSTM model performed poorly, with a training accuracy of 57.50% and a much lower validation accuracy of 30.00% (Fig. 4). This shows that the LSTM struggled not only with generalization, but also with learning patterns from the training data. These findings highlight the importance of optimizing model settings, such as fine-tuning hyperparameters, applying regularization techniques, or investigating alternative architectures, to increase performance and avoid overfitting.



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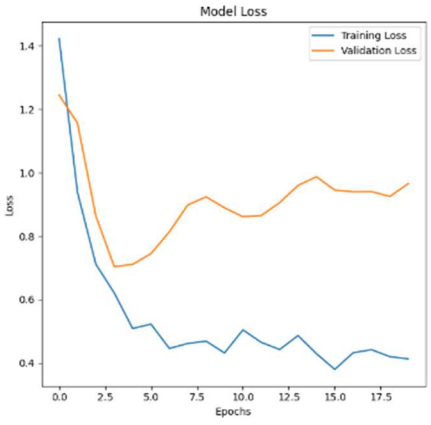
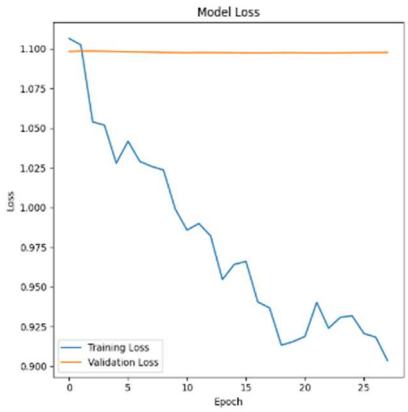


(b)

Fig. 3 CNN Model Performance. (a) Accuracy over epochs And (b) Loss over epochs

(a)



(b)

Fig. 4 LSTM Model Performance. (a) Accuracy over epochs And (b) Loss over epochs

B. Optimized Model Configurations

To further evaluate the models, hyperparameters such as sequence length (1, 5, 10) and number of epochs (50, 100, 150) were adjusted. The RNN model achieved the best results with a sequence length of 1 and 50 epochs, reaching a test accuracy of 94.99% and a test loss of 0.12 (Table I). The LSTM model, with a sequence length of 5 and 50 epochs, achieved a test accuracy of 94.74% and a test loss of 0.49 (Table II). The CNN model, with a kernel size of 3 and 150 epochs, achieved a test accuracy of 90.00% and a test loss of 0.38 (Table III).

TABLE I. ANANALYSIS OF RNN

Model	Sequence Length	Epochs	Test Accuracy	Test Loss
RNN	1	50	94.99	0.12
RNN	1	100	94.99	0.10
RNN	1	150	94.99	0.13
RNN	5	50	89.99	0.23
RNN	5	100	89.99	0.38
RNN	5	150	89.99	0.49
RNN	10	50	89.99	0.94
RNN	10	100	89.99	0.71
RNN	10	150	89.99	0.529

TABLE II. ANALYSIS OF LSTM

Model	Sequence Length	Epochs	Test Accuracy	Test Loss
LSTM	1	50	90.00	0.17
LSTM	1	100	90.00	0.15
LSTM	1	150	90.00	0.37
LSTM	5	50	94.74	0.49
LSTM	5	100	94.74	0.86
LSTM	5	150	94.74	1.29
LSTM	10	50	83.33	2.44
LSTM	10	100	77.78	7.60
LSTM	10	150	83.33	3.23

TABLE III. ANALYSIS OF CNN

Model	Kernel Size	Epochs	Test Accuracy	Test Loss
CNN	3	50	90.00	0.52
CNN	3	100	90.00	0.40
CNN	3	150	90.00	0.38
CNN	5	50	90.00	0.65
CNN	5	100	90.00	0.43
CNN	5	150	90.00	0.40
CNN	7	50	90.00	0.73
CNN	7	100	90.00	0.44
CNN	7	150	90.00	0.40

C. Precision and F1 Score Evaluation

When it came to macro accuracy, the RNN model reached the highest possible value of 0.56. It performed exceptionally well in the Normal category (precision = 1.00), and it demonstrated satisfactory performance in the Weak category (precision = 0.67). The CNN and LSTM models, on the other hand, had difficulty with the Weak and Strong categories, reaching macro precision values of 0.30 and 0.32, respectively, as shown in Table IV. The examination of the F1 score provided additional evidence of the superiority of the RNN. The RNN had a macro F1 score of 0.59, which was higher than the LSTM's score of 0.32 and the CNN's score of 0.32 (Table V). The RNN showed excellent performance in the Weak category (F1 score = 0.80), whereas the CNN and LSTM models were unable to accurately categorize any cases that were classified as Weak.

TABLE IV. COMPARISON FOR MACRO PRECISION

Model	RNN	CNN	LSTM
Precision	0.56	0.3	0.32

The RNN model demonstrated superior performance compared to the CNN and LSTM models, showcasing strong generalization capabilities and high accuracy in classifying grip strength data. Its ability to effectively handle temporal dependencies made it particularly well-suited for this task. In contrast, the CNN model struggled with temporal data, leading to overfitting and poor performance, especially in the Weak and Strong categories. Similarly, the LSTM model, despite its theoretical advantage in modeling long-term dependencies, underperformed due to its complexity and challenges in handling imbalanced data. A common issue across all models was their difficulty in accurately classifying the underrepresented Strong category, underscoring the need for improved data balancing techniques and more robust feature extraction methods to enhance model performance in future work.

Table V. Comparison for f1 score

Model	Weak Precision	Normal Precision	Strong Precision	Weak Recall	Normal Recall	Strong Recall	Weak F1	Normal F1	Strong F1	Macro F1	Weighted F1
RNN	0.667	1	0	1	0.944	0	0.8	0.971	0	0.59	0.954
CNN	0	1	0	0	0.1	0	0	0.182	0	0.061	0.182
LSTM	0	0.5	0	0	0.053	0	0	0.95	0	0.032	0.09

These results contribute to the growing body of work validating synthetic data in biomedical signal analysis. By demonstrating high performance with minimal real-world data acquisition, this work supports the practicality of simulation-driven model evaluation, especially in contexts where hardware-based data collection is costly or unfeasible.

V. CONCLUSION

This study evaluated three deep learning models—RNN, LSTM, and CNN—based on time-series sensor data to predict grip strength. The RNN model outperformed other models by achieving a test accuracy of 94.99% and a test loss of 0.190, which was attributed to its capacity to identify sequential relationships. The CNN model achieved an accuracy of 90.00%; however, it encountered challenges with time data, resulting in a test loss of 0.389. Despite its ability to manage long-term dependencies, the LSTM model demonstrated subpar results, with a test loss of 0.561, which was likely the result of overfitting and training inefficiencies. The RNN was successful in recognizing typical grip strength states;

however, all models encountered challenges with weakened and stronger states, underscoring the impact of class imbalance. The RNN's efficacy for this application was validated by its maximal macro accuracy and F1 score. Hyperparameter optimization, hybrid models that integrate RNN, CNN, and LSTM, data augmentation strategies to alleviate class imbalance, sophisticated assessment measures such as ROC-AUC and precision-recall curves, and alternative architectures such as GRUs should be the primary focus of future research. In summary, the RNN model has proven to be the most effective choice for time-series predictions in this field due to its superior efficacy in grasp strength categorization.

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