Graphene-based Wearable E-Textiles Integrated with Deep Learning for Real-Time Sweat Analysis in Military and Sports Applications

1st V Ceronmani Sharmila
Department of Electronics and Communication Engineeering
Faculty of Engineering and Technology
SRM institute of Technology
Kattankulathur, India
ceronmav@srmist.edu.in

2nd B Sai Varun
Department of Electronics and Communication Engineeering
SRM institute of Technology
Kattankulathur, India
bb0359@srmist.edu.in

3rd P A Alvis Josh
Department of Electronics and Communication Engineeering
SRM Institute of Technology
Kattankulathur, India
ap9827@srmist.edu.in

4th Aashrith Atmuri
Department of Electronics and Communication Engineeering
Communication Engineeering
SRM Institute of technology
Kattankulathur, India
aa4034@srmist.edu.in

5th K Prasanth
Department of Electronics and Communication Engineeering
Communication Engineeering
SRM Institute of technology
Kattankulathur, India
kz1117@srmist.edu.in

***Abstract*—Graphene-based conductive fabrics integrated with deep learning algorithms enable real-time sweat analysis for military and sports applications. These graphene-based e-textiles, renowned for their flexibility, durability, and bio-signal capturing capabilities, are screen-printed onto fabric to create non-invasive sweat sensors. The sensors measure physiological data such as electrolyte balance, hydration levels, and sweat rates, essential for monitoring physical performance under various conditions. A deep learning model, combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, processes the collected data to classify sweat composition and recommend optimal clothing based on environmental and physical stressors. Performance analysis demonstrates CNN's superior convergence speed and lower loss values compared to LSTM. This integrated system offers real-time feedback, helping to prevent dehydration, fatigue, and heat-related illnesses, thus providing a transformative approach to personalized healthcare and performance monitoring in demanding environments.**

***Keywords*—graphene, CNN, LSTM, bio-signal, sweat analysis.**

I. INTRODUCTION

Wearable technologies have rapidly evolved in recent years, offering significant advancements in personalized healthcare, sports performance monitoring, and military applications. Among the various developments, wearable e-textiles integrated with sensors have gained considerable attention due to their potential to non-invasively monitor physiological parameters. These smart textiles are flexible, lightweight, and comfortable, making them ideal for continuous, real-time monitoring in dynamic environments such as military operations and athletic performance. However, despite these advancements, challenges remain in terms of the durability, scalability, and efficiency of these devices, particularly when exposed to environmental stressors such as sweat, movement, and washing [1].

Graphene, a material known for its remarkable electrical, thermal, and mechanical properties, has emerged as a promising candidate for developing advanced wearable sensors. Graphene-based e-textiles, in particular, offer high conductivity, flexibility, and washability, making them suitable for integrating into garments for real-time health monitoring. The screen-printing of graphene-based inks onto textile substrates has allowed for the creation of multifunctional wearable devices capable of capturing bio-signals such as heart rate, muscle activity, and movement. Additionally, graphene's ability to interact with sweat, a natural biofluid, presents an opportunity to leverage this material for monitoring sweat composition, which can provide critical insights into an individual’s hydration levels, electrolyte balance, and overall physiological state.

Sweat analysis is becoming increasingly important in various fields, particularly in military and athletic applications, where maintaining optimal hydration and electrolyte levels is crucial for performance and safety. Dehydration and electrolyte imbalances can lead to fatigue, heat-related illnesses, and even severe medical conditions, especially in extreme environments. Traditional methods of sweat analysis often require laboratory testing and invasive sampling, which are not suitable for real-time monitoring in the field. Wearable sweat sensors, integrated into e-textiles, offer a practical solution for continuous, non-invasive monitoring, providing real-time feedback on an individual's physiological state.

To enhance the functionality of these wearable sweat sensors, the integration of advanced computational models such as deep learning has shown promise in improving the accuracy and efficiency of data interpretation. Deep learning models, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have demonstrated exceptional performance in time-series data analysis, making them well-suited for processing the continuous flow of physiological data collected by wearable sensors [2]. In this context, combining graphene-based e-textiles with deep learning models can significantly enhance the capability of sweat sensors, enabling real-time prediction and classification of sweat composition, hydration levels, and related physiological states.

The application of deep learning in wearable technologies has already shown promise in fields such as fall detection and gait analysis. These models are capable of processing large datasets and extracting critical temporal features, making

979-8-3315-2834-8/24/$31.00 ©2024 IEEE

them highly effective in detecting patterns in physiological signals. By applying a similar approach to sweat analysis, it is possible to develop a system that not only monitors current physiological conditions but also predicts future states, such as dehydration risk or the need for specific adaptive clothing, based on the individual's sweat profile and environmental factors.

In this paper, a novel system is proposed that integrates graphene-based sweat sensors into wearable e-textiles, with data processed using a CNN-LSTM deep learning model. This system is designed to provide real-time monitoring and predictive analysis of sweat composition for soldiers and athletes, helping to optimize their clothing choices and prevent heat-related illnesses. The proposed solution aims to offer a practical, scalable, and highly effective method for improving performance and safety in demanding physical environments.

The subsequent sections delve into literature review of graphene-based analysis for wearable textiles, followed by an in-depth discussion of the proposed methodology for graphene-based E-textiles for sweat analysis and deep learning model for prediction. The paper then presents the methodology and implementation before concluding with a discussion of the results.

II. Related Works

Wearable e-textiles have emerged as a significant innovation in personalized healthcare and performance monitoring. Numerous studies have explored their application in continuous, non-invasive health monitoring, with a focus on integrating sensors into textiles for real-time physiological data acquisition.

Abdelkader et al. [3] demonstrated the potential of ultra flexible and robust graphene supercapacitors printed on textiles for wearable electronics. The supercapacitors exhibited high flexibility, robustness, and capacitance retention, making them ideal for integration into wearable health monitoring systems. Their work laid the foundation for developing energy storage solutions that could be seamlessly integrated into garments.

Afroj et al. [4] explored the engineering of graphene flakes for wearable textile sensors. They developed a highly scalable and ultrafast yarn dyeing technique, enhancing the sensitivity and durability of textile sensors. This innovation supports the creation of e-textiles capable of real-time monitoring in high-performance applications.

In another study, Afroj et al. [5] focused on developing highly conductive, scalable, and machine-washable graphene-based e-textiles for multifunctional wearable electronic applications. The textiles maintained their electrical properties after repeated washing, demonstrating their practicality for long-term use in wearable health monitoring systems. Afroj et al. [6] presented graphene-based technologies for tackling COVID-19 and future pandemics, emphasizing the role of graphene e-textiles in healthcare settings. These materials could be adapted for personal protective equipment (PPE) to enhance both functionality and comfort.

Al-Khafajiy et al. [7] described the use of wearable sensors for remote health monitoring, particularly for the elderly. Their research highlights the importance of continuous, non-invasive monitoring to enhance the quality of life and ensure timely medical intervention. Beach et al. [8] evaluated the performance of graphene ECG electrodes under varying conditions. Their findings showed that graphene-based electrodes could perform comparably to traditional rigid electrodes, supporting the use of graphene in wearable medical devices.

Gao et al. [9] explored wearable and flexible electrochemical sensors for sweat analysis, summarizing the recent advancements in materials and methods for real-time, noninvasive monitoring. They highlighted the potential of sweat as a source of physiological data, offering new possibilities for personalized health monitoring. Yang et al. [10] provided a comprehensive review of long-term sweat sensors, emphasizing the importance of sampling methods, energy supply, and intelligent health monitoring. They discussed how environmental factors, including temperature and movement, play a role in sweat generation and energy harvesting, presenting challenges and future opportunities for wearable healthcare applications.

Liu et al. [11] reviewed advancements in skin-interfaced colorimetric microfluidic devices for on-demand sweat analysis. They highlighted how these devices allow real-time biomarker detection without external electronics, making them more flexible and cost-effective. The review also discussed challenges like sampling over time and future strategies for improving temporal resolution and feedback systems for wearable healthcare applications. Wang et al. [12] explored the use of epidermal wearable optical sensors for sweat monitoring. They discussed advancements in materials and designs, particularly in colorimetry, Raman spectroscopy, fluorescence, and electrochemiluminescence. The reviews of the following papers [13] [14] [15] highlighted the potential for real-time, non-invasive health monitoring through sweat analysis, emphasizing challenges and future prospects for integration with wearable devices in healthcare applications.

III. Graphene-based E-Textiles For Sweat Analysis

Graphene, a two-dimensional carbon material, is well-known for its high surface area, excellent electrical conductivity, and mechanical flexibility. In recent years, graphene-based e-textiles have gained traction as wearable sensors for monitoring physiological parameters. These textiles are lightweight, flexible, and can seamlessly integrate into regular clothing. The graphene-based e-textiles discussed in the first paper (graphene-based paper) are machine-washable and capable of sensing bio-signals such as movement and body temperature. For this research, these textiles can be modified to include sweat sensors that analyse components such as pH, sodium, potassium, and chloride levels. These sensors will be printed onto fabrics using scalable techniques like screen printing, ensuring they are durable and cost-effective for mass production. Graphene's excellent conductivity makes it ideal for capturing electrical signals produced by sweat ion interactions. The ability to monitor sweat continuously without invasive devices offers a significant advantage in environments where soldiers or athletes face extreme physical exertion. Such real-time monitoring can provide immediate feedback on hydration levels, helping prevent dehydration or other performance-limiting factors.

IV. Deep Learning For Prediction Analysis

Once the graphene-based e-textiles capture sweat data, it becomes essential to analyse and interpret the data for meaningful insights. This is where the deep learning model, inspired by the fall detection system [2], comes into play. The model can be adapted to detect patterns in the sweat data, using Convolutional Neural Networks (CNNs) to extract features and Long Short-Term Memory (LSTM) networks to understand the temporal dynamics

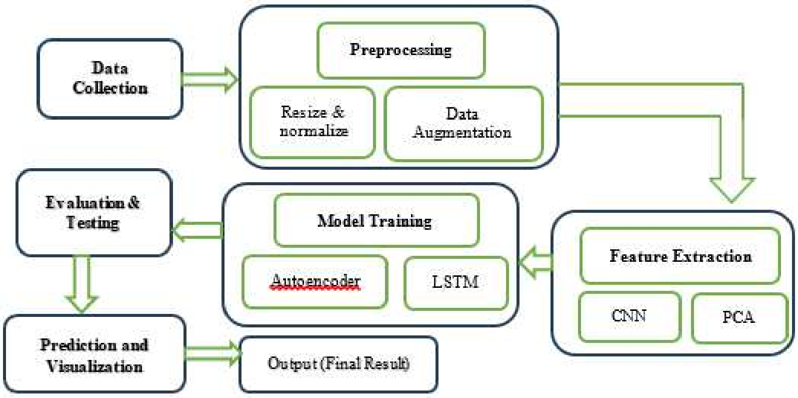

Fig. 1. CNN-LSTM Model for Prediction

The CNN-LSTM ensemble model as shown in Fig. 1, will be trained on large datasets containing sweat profiles under various conditions—such as during heavy physical activity, exposure to heat, or periods of rest. By identifying correlations between sweat composition and hydration or electrolyte imbalances, the model can predict when a soldier or athlete is likely to require intervention. For instance, if the system detects rising sodium levels or a drop in sweat pH, it could recommend specific hydration strategies or adjustments in clothing layers to enhance cooling.

A. *Methodology*

The following steps are utilized for prediction:

1) Data Collection: In this block, data is collected from graphene-based e-textiles embedded with sweat sensors. These sensors capture various parameters of sweat such as pH, electrolyte levels (sodium, potassium), and hydration levels. The real-time data is wirelessly transmitted to a central system for processing. The data also includes environmental factors such as temperature and humidity, which influence sweat production.

2) Preprocessing: Before training the model, the raw data undergoes preprocessing.

a) Resize & Normalize: The collected sweat data, often in different units, is normalized to standard scales, ensuring consistent input for the model. For instance, pH values (ranging from 0 to 14) may be rescaled between 0 and 1.

b) Data Augmentation: Since real-world datasets may be limited, data augmentation techniques can be applied. Synthetic data generation or perturbations may be used to simulate different conditions, such as varying hydration levels or extreme temperatures, enriching the dataset and helping the model generalize better.

3) Feature Extraction: This block focuses on extracting meaningful features from the raw sweat data.

a) CNN (Convolutional Neural Network): CNNs are used to automatically extract spatial features from the sweat data. For example, they can identify patterns in electrolyte levels or hydration states over time.

b) PCA (Principal Component Analysis): PCA is employed to reduce the dimensionality of the data while retaining the most important variance. This helps in simplifying the dataset, making the learning process more efficient without losing critical information.

4) Model Training

a) Autoencoder: An autoencoder is employed for unsupervised learning to encode and compress the sweat data into a lower-dimensional space, which helps in removing noise or irrelevant details. The autoencoder reconstructs the data, ensuring only essential information is retained for future analysis.

b) Long Short-Term Memory (LSTM): These networks, a type of recurrent neural network (RNN), are crucial for learning time-dependent patterns in the data. Since sweat composition changes over time, LSTMs can capture temporal correlations, helping to predict future states, such as when dehydration may occur based on current sweat conditions.

The various techniques and algorithms can be understood and visualised in the following pseudo-code.

Algorithm: LSTM Data Preprocessing
Require: Graphene dataset g, Dehydration dataset D
Ensure: Preprocessed data and LSTM model M
F_G ←Select features from g
F_D ← Select features from D
Ω ←Merge (F_G, F_D)
Remove missing values from Ω
Initialize StandardScaler σ
$X \leftarrow \sigma(\Omega)$
Reshape X: $X \leftarrow (-1,1,2)$
Split data:
$(X_{train}, X_{test}, y_{train}, y_{test})$←
    train_test_split(X,test_size=0.2)
Construct LSTM model M:
M ←Sequential (LSTM (64), Dense (32), Dense (2))
return M, X_{train}, X_{test}

V. Results And Discussion

The Sweat Sensor dataset is used for evaluating the model.

Around 500 images were used for evaluation. The training and testing split was 80: 20. The combination of CNN and LSTM algorithm was implemented for predicting the model.

A. CNN Accuracy Calculation:

The first graph (Fig.2) shows the training and validation accuracy over 10 epochs for a Convolutional Neural Network (CNN).

1) Training Accuracy (blue line): Initially, the training accuracy increases rapidly, especially during the first two epochs, and continues to rise until around epoch 6.

After epoch 6, the training accuracy reaches a high value of nearly 1.0, indicating that the model is performing extremely well on the training data, potentially even overfitting, as it achieves near-perfect accuracy.

2) Validation Accuracy (orange line): The validation accuracy also improves during the first few epochs, reaching a peak by about epoch 3. However, after that, the validation accuracy plateaus or even decreases slightly.

This indicates that while the model performs well on the training data, it does not generalize as well to the validation set after epoch 3, showing a sign of overfitting.

3) Potential Overfitting: The gap between training and validation accuracy after epoch 3 suggests overfitting. The model has learned the training data well, but its ability to perform on unseen validation data does not improve further, or even declines slightly after a few epochs.

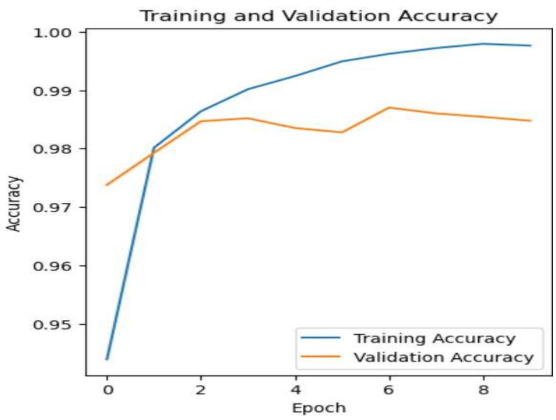

Fig. 2. Training and Validation Accuracy of CNN model

B. CNN Loss Calculation

The second graph (Fig.3) represents the Training and Validation Loss across 10 epochs for a Convolutional Neural Network (CNN).

1) Training Loss (blue line): The training loss decreases rapidly within the first few epochs, which shows that the model is learning quickly during the early stages of training.

After around 2-3 epochs, the training loss continues to decrease gradually, reaching a very low value towards the final epochs. This indicates that the model fits the training data increasingly well, with nearly perfect performance by the end.

2) Validation Loss (orange line): The validation accuracy also improves during the first few epochs, reaching a peak by about epoch 3. However, after that, the validation accuracy plateaus or even decreases slightly.

The validation loss initially decreases similarly to the training loss, indicating that the model generalizes well to the validation data at first.

Around epoch 3-4, the validation loss starts to fluctuate and stops decreasing significantly. This can be a sign of overfitting, where the model performs very well on the training data but struggles to generalize as well on unseen data.

By the later epochs (after epoch 5), the validation loss either remains steady or increases slightly, confirming the overfitting trend observed.

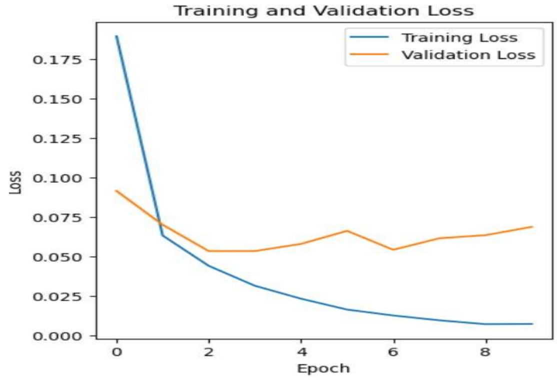

Fig. 3. Training and Validation Loss of CNN model

C. LSTM-Training and Validation MAE

The third graph (Fig.4.) illustrates the Mean Absolute Error (MAE) for both training and validation data over 50 epochs, obtained by training a model using an LSTM (Long Short-Term Memory) network.

1) Training MAE (blue line): The training MAE starts relatively high (around 0.45) and decreases rapidly within the first few epochs, suggesting that the LSTM model is quickly learning and adjusting to the training data.

After the first few epochs, the training MAE stabilizes around 0.05 to 0.08, with slight fluctuations, but it remains low throughout the rest of the epochs, indicating that the model is consistently improving and learning the training data well.

2) Validation MAE (orange line): The validation MAE follows a similar pattern, initially decreasing sharply, showing that the model generalizes well to unseen data in the early stages of training.

By around epoch 5, the validation MAE stabilizes and fluctuates around 0.05, which is close to the training MAE. This is a good sign, as it suggests that the model is not overfitting and is generalizing well on the validation set.

There are some minor fluctuations in the validation MAE, but these appear to be small, indicating stable generalization performance.

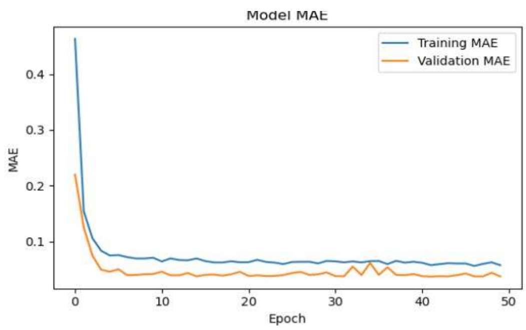

Fig. 4. MAE for Training and Validation Data

D. LSTM-Training and Validation Loss

The fourth graph (Fig.5) represents the Training and Validation Loss across 50 epochs for a model trained using an LSTM (Long Short-Term Memory) network. Here's the interpretation:

1) Training Loss (blue line): The training loss starts high (around 0.27) and decreases sharply in the first few epochs. This indicates that the model is learning rapidly and minimizing the error on the training data early in the process.

After the initial drop, the training loss stabilizes at a very low value close to zero (around 0.005) for the remainder of the training epochs, indicating that the model has effectively minimized the loss on the training data.

2) Validation Loss (orange line): The validation loss follows a similar trend to the training loss. It decreases sharply within the first few epochs, indicating that the model is also generalizing well to the validation data early in the training.

After epoch 5, the validation loss stabilizes, remaining at a similarly low value, almost identical to the training loss. This shows that the model is not only learning well but also generalizing to the validation set effectively.

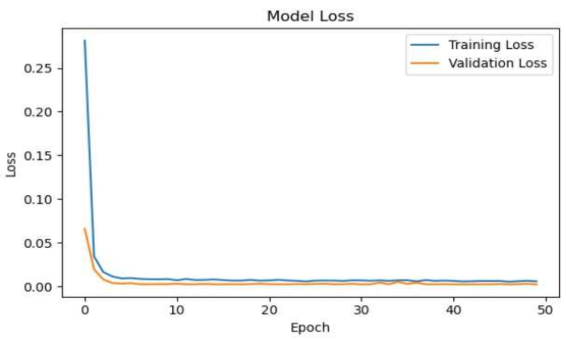

Fig. 5. MAE for Training and Validation Loss

E. Comparison

Table 1 provides the comparative analysis of various models. The following graphs (Fig.6 and Fig.7) represent a comparison of the performance between CNN (Convolutional Neural Network) and LSTM (Long Short-Term Memory) models in terms of accuracy and loss during training and validation over several epochs.

The interpretation of the fifth graph is given below.

1) CNN Training Accuracy (blue line): The CNN model quickly achieves high training accuracy within the first few epochs and continues to improve slightly. By the end of training, it reaches nearly 1.0, indicating near-perfect accuracy on the training data.

2) CNN Validation Accuracy (orange line): The validation accuracy for CNN improves rapidly, stabilizing around 0.98 after a few epochs, demonstrating good generalization to unseen data without significant overfitting.

3) LSTM Training Accuracy (green line): The LSTM model starts with lower accuracy compared to CNN but improves rapidly, reaching around 0.98 accuracy by epoch 5. After the initial jump, the training accuracy plateaus, showing that the model has effectively learned the training patterns.

4) LSTM Validation Accuracy (red line): The LSTM validation accuracy steadily improves, reaching close to 0.98 by epoch 5. It fluctuates slightly but remains near CNN's validation accuracy, indicating good generalization.

The interpretation of the sixth graph is given below.

5) CNN Training Loss (blue line): The CNN training loss decreases rapidly within the first few epochs, approaching near-zero values by the end of training, indicating that the model effectively learns the patterns in the training data.

6) CNN Validation Loss (orange line): The CNN validation loss drops significantly in the first few epochs and stabilizes at a very low value, suggesting excellent generalization to unseen data with minimal error.

TABLE I. COMPARISON TABLE

Machine Learning Models	Average Accuracy	F1-Score
CNN (model A)	83.34	82.67
CNN (model B)	84.56	83.89
LSTM (model A)	85.45	84.34
LSTM (model B)	86.78	85.56
Hybrid CNN-LSTM (model A)	88.45	87.23
Hybrid CNN-LSTM (model B)	89.12	88.01
Proposed Ensemble	92.15	91.78

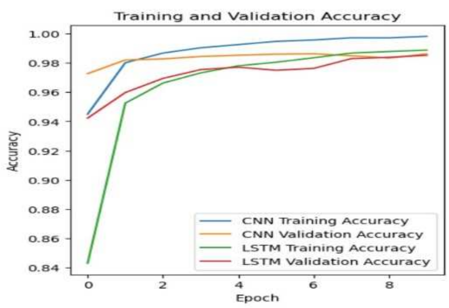

Fig. 6. Training and Validation Accuracy Over Epochs

7) LSTM Training Loss (green line): The LSTM training loss starts higher

CNN but drops significantly after a few epochs. However, it doesn't reach the same low values as CNN, implying that LSTM doesn't learn the training data as perfectly as CNN.

8) LSTM Validation Loss (red line): The LSTM validation loss decreases significantly but fluctuates more than CNN after epoch 5. It remains slightly higher than CNN's validation loss, indicating that LSTM may struggle more with generalization.

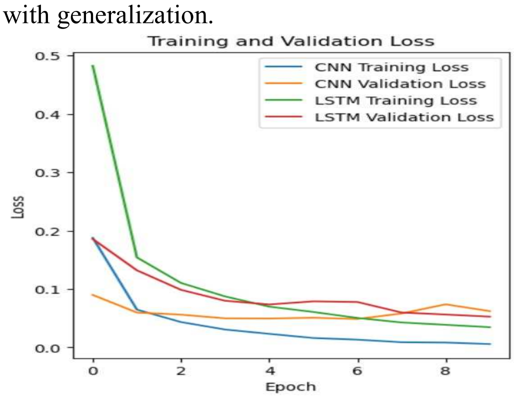

Fig. 7. Training and Validation Loss Over Epochs

VI. CONCLUSIONS

This research proposes a highly innovative solution by integrating graphene-based e-textiles with deep learning models for sweat analysis. By combining the strengths of graphene's conductive properties with the predictive capabilities of advanced neural networks, a smart clothing tailored to real-time physiological monitoring can be developed. This solution addresses the challenges faced by soldiers and athletes who operate in extreme conditions, offering customized recommendations for hydration, clothing, and performance optimization.

The analysis of the provided graphs comparing CNN and LSTM models shows that both models exhibit strong learning performance, though CNN tends to outperform LSTM slightly in terms of faster convergence and lower loss. CNN reaches near-perfect training accuracy quickly and maintains consistent validation accuracy with minimal error, indicating robust generalization to unseen data. LSTM, while also achieving high accuracy, starts with higher training and validation loss compared to CNN, which suggests it might struggle a bit more in learning the training data perfectly. However, both models show stable performance after the initial few epochs, with CNN consistently showing lower training and validation loss values. Overall, CNN demonstrates better learning efficiency and generalization capabilities, making it the superior model in this comparison. The outcome of this work will contribute to the field of wearable technology and personalized healthcare, paving the way for the next generation of intelligent apparel that can monitor and respond to the body's needs. These developments will not only enhance physical performance but also provide critical health safeguards in demanding environments. Future research could explore integrating additional biosensors with graphene-based e-textiles and enhancing deep learning models for more comprehensive physiological monitoring and predictive analytics.

REFERENCES

[1] Islam, M. R., Afroj, S., Beach, C., Islam, M. H., Parraman, C., Abdelkader, A., Casson, A. J., Novoselov, K. S., & Karim, N., "Fully printed and multifunctional graphene-based wearable e-textiles for personalized healthcare applications," iScience, vol. 25, no. 3, pp. 103945, Mar. 2022.

[2] R. Jain and V. B. Semwal, "A Novel Feature Extraction Method for Preimpact Fall Detection System Using Deep Learning and Wearable Sensors," in IEEE Sensors Journal, vol. 22, no. 23, pp. 22943-22951, Dec. 2022.

[3] Abdelkader, A.M., Karim, N., Valle´ s, C., Afroj, S., Novoselov, K.S., and Yeates, S.G., "Ultraflexible and robust graphene supercapacitors printed on textiles for wearable electronics applications," 2D Mater. vol.4, no.3, 035016, July 2017.

[4] Afroj, S., Karim, N., Wang, Z., Tan, S., He, P., Holwill, M., Ghazaryan, D., Fernando, A., and Novoselov, K. S., "Engineering Graphene Flakes for Wearable Textile Sensors via Highly Scalable and Ultrafast Yarn Dyeing Technique," ACS Nano, vol. 13, no. 3, pp. 3847–3857, Mar. 2019.

[5] Afroj, S., Tan, S., Abdelkader, A. M., Novoselov, K. S., & Karim, N., "Highly conductive, scalable, and machine washable graphene-based e-textiles for multifunctional wearable electronic applications," Advanced Functional Materials, vol. 30, no. 23, 2000293, April 2020.

[6] Afroj, S., Britnell, L., Hasan, T., Andreeva, D.V., Novoselov, K.S., and Karim, N., "Graphene-based technologies for tackling COVID-19 and future pandemics," Adv. Funct. Mater. vol. 31, no.52, 2107407, Sep. 2021.

[7] Al-khafajiy, M., Baker, T., Chalmers, C., Asim, M., Kolivand, H., Fahim, M., & Waraich, A., "Remote health monitoring of elderly through wearable sensors," Multimedia Tools and Applications, vol. 78, no. 17, pp. 24681–24706, Jan. 2019.

[8] C. Beach, N. Karim and A. J. Casson, "Performance of graphene ECG electrodes under varying conditions," 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, pp. 3813-3816, 2018.

[9] Gao, F., Liu, C., Zhang, L., Liu, T., Wang, Z., Song, Z., Cai, H., Fang, Z., Chen, J., Wang, J., Han, M., Wang, J., Lin, K., Wang, R., Li, M., Mei, Q., Ma, X., Liang, S., Gou, G., & Xue, N., "Wearable and flexible electrochemical sensors for sweat analysis: a review," Microsystems & Nanoengineering, vol. 9, no. 1, pp. 1–21, Jan. 2023.

[10] Yang, P., Wei, G., Liu, A., Huo, F., & Zhang, Z., "A review of sampling, energy supply and intelligent monitoring for long-term sweat sensors," npj Flexible Electronics, vol. 6, no. 33, pp. 1–11, 2022.

[11] Liu, W., Cheng, H., & Wang, X., "Skin-interfaced colorimetric microfluidic devices for on-demand sweat analysis," npj Flexible Electronics, vol. 7, no. 43, pp. 1-9, 2023.

[12] Wang, J., Luo, Y., Zhou, Z., Xiao, J., Xu, T., & Zhang, X., "Epidermal wearable optical sensors for sweat monitoring," Communications Materials, vol. 5, no. 77, pp. 1–11, Mar. 2024.

[13] W Yuce, M.R., Ng, P.C., and Khan, J.Y. (2008). Monitoring of physiological parameters from multiple patients using wireless sensor network. J. Med. Syst. 32, 433–441.

[14] Zhang, H., Qiao, Y., and Lu, Z. (2016). Fully printed ultraflexible supercapacitor supported by a single-textile substrate. ACS Appl. Mater. Inter. 8, 32317–32323.

[15] Zhang, M., Zhao, M., Jian, M., Wang, C., Yu, A., Yin, Z., Liang, X., Wang, H., Xia, K., Liang, X., et al. (2019). Printable smart pattern for multifunctional energy-management E-textile. Matter 1, 168–179.