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PAIN RECOGNITION WITH PHYSIOLOGICAL SIGNALS USING HYBRID MODELS

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***Abstract*— Medical care is one of the most crucial sectors, yet effective pain identification has always been a problem since it remains highly dependent on manual primary feature engineering by doctors. Physiological cues are an important source of pain assessment data, and conventional analysis has a tendency to restrict scalability and accuracy. In this regard, the proposed research proposes a pain detection mechanism that is automatic and relies on advanced deep learning models without requiring the involvement of manual feature engineering. The approach is useful to Hashtagify features and classify them together in hybrid structures, e.g., CNN+BiLSTM+GRU and a Stacking Classifier. Using multi-level contextual information over uni-level features used in the current models, the models are able to detect more nuanced patterns in the physiological signals and so enhance discrimination between the pain and no-pain states. The critical performance measures such as accuracy, efficiency and interpretability were tested on the framework. The outcome of the comparison reveals that Stacking Classifier had the best recognition accuracy of 99 percent, and hybrid CNN+BiLSTM+GRU model demonstrated good feature learning and their performance was stable. This study identifies the accuracy/model complexity dilemma and makes timely recommendations on the selection of effective approaches to automatic pain detection. The suggested system facilitates more effective pain assessment in medicine in a combination of both efficiency and accessibility.**

Keywords—***Deep learning, stacking classifier, pain classification, hybrid models, Automatic pain detection.***

I NTRODUCTION

Suffering is an inevitable biological process and is often a feature of such a disease that needs medical attention. Conventionally, the assessment of pain has been based on individual observation of the patient to observe the subjective signs on which healthcare professionals use them to interpret behavior and verbal report. Physiotherapists, in their turn, follow up patients during exercises and modulate treatments. However, these tests are not standardized and subjective and thus the system that would be capable of objective recognition and automation of pain status would come in handy.

Automated pain detection is based on a distinction between pain and non-pain states on the basis of behavior and physiology. Body language, gestures and speech are informative but not necessarily dependable because people can always hide the pain or fail to do so because of their personality or because they lost the control of their senses [4]. Physiological signals, however, give more consistent information. The responses such as the refreshing of the skin conductance, some adjustment of the cardiac frequency variability, blood pressure changes and the muscular activity, are the prescribed responsiveness of pain under the influence of neural and metabolic functioning. Such signals have been possible to investigate due to databases like BioVid and Emo Pain, in which electrodermal activity (EDA), electrocardiogram (ECG) and electromyogram (EMG) are frequently measured in studies.

Recently, the high potential of deep learning techniques has benefited pain detection, therefore, surpassing the conventional methods, the hand division of the elements to be examined by (medical) professionals. Deep learning techniques are able to learn to encode intricate contextual features of the uncoded physiological data, such as temporal dynamics across different time scales of short-term variations to long-term patterns. We present the deep learning-enforced pain/no pain discrimination system based on physiological measurements in this paper. The BioVid Heat Pain Database and Emo Pain 2021 database are used to assess the model with the purpose of obtaining the objective and effective approach to pain detection task, which may be later applied to the task of monitoring of the health status and the rehabilitation of patients.

II LITERATURE SURVEY

Pain is an intricate issue both sensory and affective, and therefore it is hard to measure in babies, anesthetized patients and incapacitated individuals. The conventional tools such as questionnaires and visual analogue scales are highly used but are generally not dependable, particularly the panel of patients with cognitive deficiencies [1], [2]. To counter such limitations, recent studies aim at automated recognition systems that are able to extract pain features from

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multimodal data. By combining physiological signals, behavioural cues, and machine learning algorithms, such systems promise to provide objective, reproducible, and clinically practical pain measurement. BioVid Heat Pain Database is one of the most widely used databases for testing and training automatic pain detection systems. It provides visual and physiological signals collected under controlled heat-stimulated conditions, providing robust benchmarking of detection models [2],[16],[24]. Experiments on this database have shown face reactions varying with pain intensity as well as expressiveness of subjects. While expressive subjects can be differentiated reliably, non-expressive subjects have more compromised signals and therefore the significance of personalization in recognition processes [5].

Real-time and objective pain monitoring has also been addressed from the viewpoint of multimodal integration of biomedical and behavioural signals. In another study [6], video-based head and facial movement signals were combined with physiological signals such as galvanic skin response, electromyography, and electrocardiography, with improved detection performance on BioVid data. Besides generic models, personalization strategies have also been explored for pain intensity estimation with higher accuracy. Using meta-information, personality traits, and homogeneity between individuals, specialized classifiers can be built to achieve higher efficiency and accuracy compared to general models [8]. Such approaches enable real-time feasibility by having diverse feature extraction pipelines and incrementally processed data. Apart from classification of pain, research has also been focused on pain intensity estimation. A method proposed in [9] used physiological signals such as blood volume pulse (BVP), electrocardiogram (ECG), and skin conductance level (SCL) obtained through external electrical stimulation. The system's pipeline involved signal preprocessing, feature extraction, and dimensionality reduction using genetic algorithms and principal component analysis.

Genetic algorithm based feature selection and PCA based feature reduction was combined to get a subset of brief and highly discriminative features. Three classifiers, i.e. linear discriminant analysis, k-nearest neighbour, and support vector machine were compared under various conditions such as multi-signal, multi-subject, and multi-day conditions. The models that were matched steadily with more than 75 percent accuracy with four pain intensity classes as compared to the probability of chance. These findings offer evidence to the capability of the method to offer objective and quantitative measurement of the pain, with the implication of the development of wearable solutions to be used in a clinical setting.

III.MATERIALS AND METHODS

The new system provides a high level pain identification model, which combines ensemble methods and deep learning to evade the fallacies of the conventional evaluation procedures. Traditional approach to the measurement of pain is based on subjective observation or handcrafted feature extraction, which is not very reliable and time-consuming. However, in contrast, the system discovers important patterns automatically using multimodal signals like face expressions, body movements, physiological signals and vocalization, without using handcrafted features.

The focal architecture of the middle makes use of hybrid deep models to learn spatial and temporal features of signals. A CNN+BiLSTM model is trained on spatial characteristics of convolutional layers and time series associations of recurrent layers. A better accuracy is also achieved using an augmented CNN+BiLSTM +GRU model to learn deep features, and a Stacking Classifier ensemble that can use multiple models in the prediction. Preprocessing of data such as normalization and cleaning provides quality input then the dataset is split into training and test sets to build the model. According to measures of the performance and confusion matrices, the system has high recognition accuracy. It is written in the Flask framework using SQLite and allows real time and lightweight testing and simplicity in the clinics. The design offers an easy, scalable, and efficient solution to pain monitoring technology that allows health care providers to offer more accurate and patient-centred care.

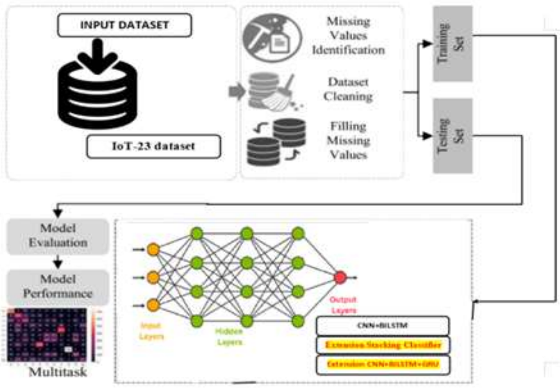

Figure1: Proposed architecture of hybrid models.

A. DATASET DESCRIPTION

To gain familiarity with the dataset, its structure, attributes, and overall composition were first examined by checking formats, dimensions, and statistical properties. The BioVid Heat Pain Database [2] is a multimodal collection containing both facial video recordings and physiological measurements. In this study, healthy volunteers were exposed to controlled thermal stimuli to elicit different pain levels. The responses were grouped into five categories: Pain 0, Pain 1, Pain 2, Pain 3, and Pain 4, where Pain 0 corresponds to the absence of pain. This graded labeling enables the training and evaluation of automated systems for recognizing and differentiating pain intensities.

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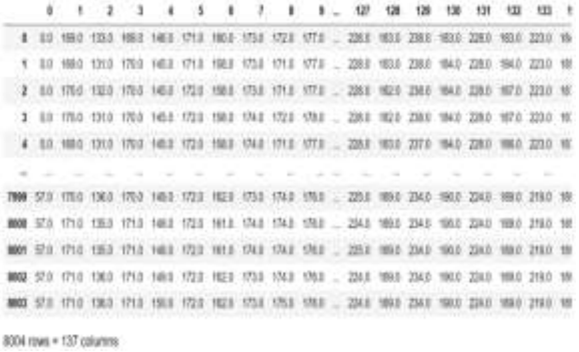

Figure2: Sample Dataset.

A **Data Processing:**

The processing of the data involves purging, organizing and transforming raw information to a format that is useful in analysing and training models where consistency and dependability are maintained. Pre-processing of BioVid Heat Pain Database In the study, the pre-processing of the BioVid Heat Pain Database consisted of the video-distribution into normalized frames and pre-processing of physiological signals (ECG, EMG, BVP) in order to remove noise. Pain labels (Pain 0–Pain 4) were aligned with the respective data, forming a structured multimodal dataset for feature extraction and model development.

B **Feature selection:**

Feature selection is the process of discovering and keeping the most relevant, informative, and non-redundant features to be used in model building. As datasets become larger and more complex, it is increasingly crucial to lower the number of input variables. The principal objective of feature selection is to enhance the predictive power of models while reducing computational expense. As a central aspect of feature engineering, it aims at choosing features that contribute most towards the learning process. By pre-filtering out irrelevant or redundant features, feature selection simplifies the dataset so that the machine learning algorithm operates on the most significant inputs alone, instead of leaving feature significance for the model to decide upon.

VI ALGORITHMS

1 RANDOM FOREST:

Random Forest is a learning ensemble algorithm that constructs several decision trees to predict pain by evaluating physiological and behaviour data. All trees vote for the presence of pain, and the decision is based on the majority vote. It enhances accuracy and avoids overfitting relative to individual models. It works well with intricate medical data and improves real-time detection of pain. Its efficiency and robustness make it appropriate for pain recognition systems in health care applications

Figure 3: Algorithm for Random forest.

2. CNN + BILSTM:

The CNN + BiLSTM approach integrates convolutional layers to learn spatial features and bidirectional LSTM to learn temporal dependencies from physiological signals. The hybrid model learns complex spatial-temporal patterns end-to-end, enhancing accuracy in pain detection. It sequentially processes preprocessed data, which suits real-time robust classification without feature engineering [30].

Figure 4: Algorithm for CNN + BILSTM.

3. CNN + BILSTM + GRU:

The CNN + BiLSTM + GRU model improves pain detection by integrating convolutional layers to extract spatial features with bidirectional LSTM and GRU layers to identify complex temporal patterns. The multi-level feature optimization enhances the accuracy and robustness of the model in processing physiological signals. The model learns from raw data end-to-end without feature selection, and this makes it highly suitable for real-time automatic pain detection in clinical applications.

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```
#create extension model using CNN1D + BILSTM + GRU as each algorithm has its own implementation of fet
#BILSTM will extract optimize features from CNN and then GRU will extract features BILSTM so will have
#optimization algorithm so will get best accuracy
extension_model = Sequential()
#create CNN1D layer with 32 neurons for data filteration and pool size as 3
extension_model.add(Conv1D(filters=32, kernel_size = 3, activation = 'relu', input_shape = (X_train.sh
extension_model.add(Conv1D(filters=64, kernel_size = 2, activation = 'relu'))
extension_model.add(Conv1D(filters=128, kernel_size = 2, activation = 'relu'))
extension_model.add(MaxPooling1D(pool_size = 1))
extension_model.add(Flatten())
extension_model.add(RepeatVector(2))
#adding LSTM Bidirectional layer to obtained optimized features from CNN
extension_model.add(Bidirectional(LSTM(32, activation = 'relu', return_sequences=True)))
#now bidirectional GRU will extract optimized fetaures from BI-LSTM and then train a model with below p
extension_model.add(Bidirectional(GRU(64, activation = 'relu')))
extension_model.add(Dropout(0.2))
#define output prediction layer
extension_model.add(Dense(units = 100, activation = 'softmax'))
extension_model.add(Dense(units = y_train.shape[1], activation = 'softmax'))
#compile and train the model
extension_model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics = ['accuracy'])
```

Figure 5: Algorithm for CNN + BILSTM + GRU.

4. STACKING CLASSIFIER:

Stacking is an ensemble learning method in which several base classifiers are blended together for enhanced predictive accuracy. In a Stacking Classifier, predictions of several different classifiers are fed as input features to a meta-classifier, which finally makes the prediction. In the system proposed here, a Stacking Classifier could blend the outputs of models learned from Random Forest, CNN + BILSTM, and CNN + BILSTM + GRU to provide a stronger and more accurate pain recognition system, taking advantage of each model's respective strengths.

Stacking Classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from lightgbm import LGBMClassifier
from sklearn.ensemble import StackingClassifier

estimators = [('rf', RandomForestClassifier(n_estimators=10)),('dt', DecisionTreeClassifier())]

clf = StackingClassifier(estimators=estimators, final_estimator=LGBMClassifier())

# fit the model
clf.fit(X_test, y_test)

y_pred = clf.predict(X_test)

stac_acc_a = accuracy_score(y_test,y_pred)
stac_prec_a = precision_score(y_test,y_pred,average='macro')
stac_rec_a = recall_score(y_test,y_pred,average='macro')
stac_f1_a = f1_score(y_test,y_pred,average='macro')
```

Figure 6: Algorithm for Stacking classifier.

IV EXPERIMENTAL RESULTS

Precision:

Precision quantifies how well the model predicts for a given level of pain, demonstrating the percentage of incorrect-free predictions out of all instances that are labeled as that level. High precision guarantees low false positive values, working toward giving correct and safe pain measurements.

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

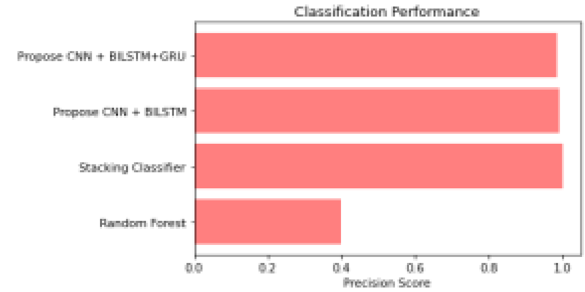

Figure 7 Precision comparison graph.

Recall:

Recall gauges how well the model detects all true occurrences of a pain level, representing the number of true pain instances detected correctly. High recall means fewer omitted instances of pain, which enables earlier and proper intervention.

$$Recall = \frac{TP}{TP + FN}$$

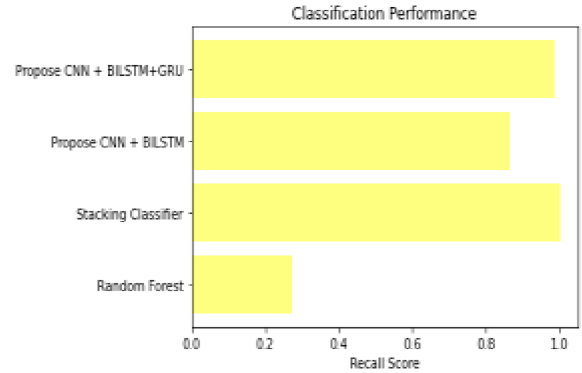

Figure 8 Recall comparison graph.

Accuracy:

Accuracy quantifies the overall accuracy of the model by evaluating the proportion of all correct pain level predictions out of all predictions. High accuracy reflects that the system consistently classifies pain levels for all patients and samples.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

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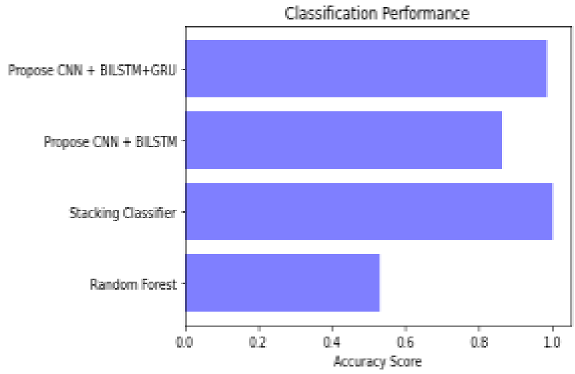

Fig 9 Accuracy graph

F1 Score:

F1-score is the harmonic mean of precision and recall, trade-off false positives and false negatives. High F1-score indicates both correct and complete pain level detection, enhancing system reliability.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

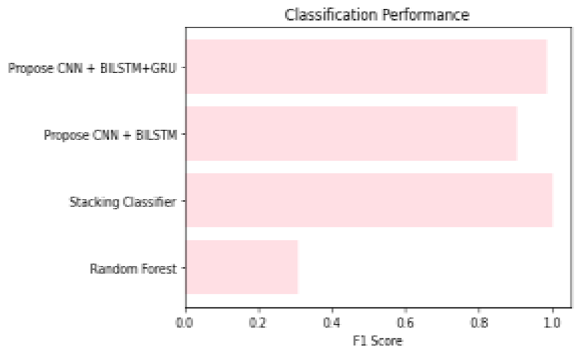

Figure 10 F1Score.

ML Model	Accuracy	Precision	f1_score	Recall
Random Forest	0.530	0.398	0.309	0.274
Extension Stacking Classifier	0.999	0.999	0.999	0.998
Propose CNN + BILSTM	0.561	0.991	0.903	0.861
Extension CNN + BILSTM+GRU	0.984	0.984	0.954	0.954

Figure 11 Performance Evaluation

Figure 12 Home page.

Figure 13 Sign-in page.

Figure14 Login page.

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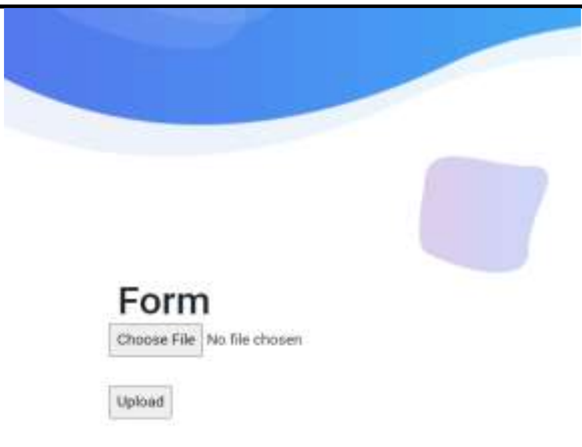

Figure 15 User input.

Figure 16 Predict result for given input.

V CONCLUSION

Deep learning models have the exceptional capability of learning complex, underlying patterns directly from raw physiological signals without manual feature extraction. Through hybrid architectures that examine physiological data at multiple levels, these models are able to detect slight variations and complex relationships within the signals, which enhances pain classification. The integration of various physiological measures like electrodermal activity and electrocardiogram results in a more rich, multi-dimensional representation of the body's pain response. This multimodal and multilevel representation greatly improves the performance of the model in comparison to traditional single-feature methods. The deep learning framework therefore presents a potent, objective, and efficient solution for effective pain recognition with the potential to revolutionize clinical pain assessment and patient care outcomes.

FUTURE SCOPE

The suggested work can further develop and enhance latent sequence information in physiological signals towards more detailed and precise pain identification. Through an examination of deeper spatial and temporal architectures, the system can more effectively capture complex dependencies and rich characteristics present in the data. The suggested method can also be used with a variety of datasets and compared with other techniques to evaluate its applicability over various healthcare settings. The addition of other signals like EMG and ECG would improve robustness through more detailed physiological information. Besides recognition of pain, the method has potential for use in emotion recognition and stress detection. Lastly, combining real-time monitoring with feedback can facilitate real-time intervention, enhancing timely and individualized care.

REFERENCES

[1] P. Werner, D. Lopez-Martinez, S. Walter, A. Al-Hamadi, S. Gruss, and R. W. Picard, ‘‘Automatic recognition methods supporting pain assessment: A survey,’’ IEEE Trans. Affect. Comput., vol. 13, no. 1, pp. 530–552, Jan. 2022.

[2] S. Walter, S. Gruss, H. Ehleiter, J. Tan, H. C. Traue, S. Crawcour, P. Werner, A. Al-Hamadi, and A. O. Andrade, ‘‘The biovid heat pain database data for the advancement and systematic validation of an automated pain recognition system,’’ in Proc. IEEE Int. Conf. Cybern. (CYBCO), Jun. 2013, pp. 128–131.

[3] Y. LeCun, Y. Bengio, and G. Hinton, ‘‘Deep learning,’’ Nature, vol. 521, no. 7553, pp. 436–444, Sep. 2015.

[4] T. Olugbade, R. Sagoleo, S. Ghisio, N. Gold, C. D. C. Amanda, B. D. Gelder, A. Camurri, G. Volpe, and N. Bianchi-Berthouze, ‘‘The affectmove 2021 challenge—Affect recognition from naturalistic movement data,’’ in Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW), Sep./Oct. 2021, pp. 1–5.

[5] P. Werner, A. Al-Hamadi, and S. Walter, ‘‘Analysis of facial expressiveness during experimentally induced heat pain,’’ in Proc. 7th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW), Oct. 2017, pp. 176–180.

[6] P. Werner, A. Al-Hamadi, R. Niese, S. Walter, S. Gruss, and H. C. Traue, ‘‘Automatic pain recognition from video and biomedical signals,’’ in Proc. 22nd Int. Conf. Pattern Recognit., Aug. 2014, pp. 4582–4587.

[7] L. Breiman, ‘‘Random forests,’’ Mach. Learn., vol. 45, no. 1, pp. 5–32, 2001.

[8] M. Kachele, P. Thiam, M. Amirian, F. Schwenker, and G. Palm, ‘‘Methods for person-centered continuous pain intensity assessment from biophysiological channels,’’ IEEE J. Sel. Topics Signal Process., vol. 10, no. 5, pp. 854–864, Aug. 2016.

[9] Y. Chu, X. Zhao, J. Han, and Y. Su, ‘‘Physiological signal-based method for measurement of pain intensity,’’ Front. Neurosci., vol. 11, p. 279, May 2017.

[10] R. A. Fisher, ‘‘The use of multiple measurements in taxonomic problems,’’ Ann. Eugenics, vol. 7, no. 2, pp. 179–188, 1936.

[11] S. Abe, Support Vector Machines for Pattern Classification, vol. 2. London, U.K.: Springer, 2005.

[12] F. Pouromran, S. Radhakrishnan,‘‘Exploration of physiological sensors, features, and machine learning models for pain intensity estimation,’’ PLoS ONE, vol. 16, no. 7, Jul. 2021, Art. no. e0254108.

[13] A. Smola and B. Schölkopf, ‘‘A tutorial on support vector regression,’’ Statist. Comput., vol. 14, no. 3, pp. 199–222, 2014.

[14] T. Chen and C. Guestrin, ‘‘XGBoost: A scalable tree boosting system,’’ in Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, 2016, pp. 785–794.

[15] F. Pouromran, Y. Lin, and S. Kamarthi, ‘‘Personalized deep bi-LSTM RNN based model for pain intensity classification using EDA signal,’’ Sensors, vol. 22, no. 21, p. 8087, Oct. 2022.

[16] D. Lopez-Martinez and R. Picard, ‘‘Multi-task neural networks for personalized pain recognition from physiological signals,’’ in Proc. 7th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW), Oct. 2017, pp. 181–184.

[17] D. Lopez-Martinez and R. Picard, ‘‘Continuous pain intensity estimation from autonomic signals with recurrent neural networks,’’ in Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Jul. 2018, pp. 5624–5627.

[18] R. Wang, K. Xu, H. Feng, and W. Chen, ‘‘Hybrid RNN-ANN based deep physiological network for pain recognition,’’ in Proc. 42nd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), Jul. 2020, pp. 5584–5587.

[19] S. D. Subramaniam and B. Dass, ‘‘Automated nociceptive pain assessment using physiological signals and a hybrid deep learning network,’’ IEEE Sensors J., vol. 21, no. 3, pp. 3335–3343, Feb. 2021.

[20] P. Thiam, P. Bellmann, H. A. Kestler, and F. Schwenker, ‘‘Exploring deep physiological models for nociceptive pain recognition,’’ Sensors, vol. 19, no. 20, p. 4503, Oct. 2019.

[21] P. Thiam, H. Hihn, D. A. Braun, H. A. Kestler, and F. Schwenker, ‘‘Multi-modal pain intensity assessment based on physiological signals: A deep learning perspective,’’ Frontiers Physiol., vol. 12, Sep. 2021, Art. no. 720464.

[22] D. Bahdanau, K. Cho, and Y. Bengio, ‘‘Neural machine translation by jointly learning to align and translate,’’ 2014, arXiv:1409.0473.

[23] I. K. M. Jais, A. R. Ismail, and S. Q. Nisa, ‘‘Adam optimization algorithm for wide and deep neural network,’’ Knowl. Eng. Data Sci., vol. 2, no. 1, pp. 41–46, 2019.

[24] S. Gruss, R. Treister, P. Werner, H. C. Traue, S. Crawcour, A. Andrade, and S. Walter, ‘‘Pain intensity recognition rates via biopotential feature patterns with support vector machines,’’ PLoS ONE, vol. 10, no. 10, Oct. 2015, Art. no. e0140330.

[25] S. Walter, S. Gruss, K. Limbrecht-Ecklundt, H. C. Traue, P. Werner, A. Al-Hamadi, N. Diniz, G. M. D. Silva, and A. O. Andrade, ‘‘Automatic pain quantification using autonomic parameters,’’ Psychol. Neurosci., vol 7, pp. 363–380, Jan. 2014.

[26] A. Andrade, P. Kyberd, and S. Nasuto, ‘‘The application of the Hilbert spectrum to the analysis of electromyographic signals,’’ Inf. Sci., vol. 178, no. 9, pp. 2176–2193, May 2008.

[27] A. O. Andrade, S. J. Nasuto, and P. Kyberd, ‘‘Extraction of motor unit action potentials from electromyographic signals through generative topographic mapping,’’ J. Franklin Inst., vol. 344, nos. 3–4, pp. 154–179, May 2007.

[28] M. S. Aung, S. Kaltwang, B. Romera-Paredes, B. Martinez, and A. Singh, ‘‘The automatic detection of chronic pain-related expression: Requirements, challenges and the multimodal EmoPain dataset,’’ IEEE Trans. Affect. Comput., vol. 7, no. 4, pp. 435–451, Oct. /Dec. 2016.

[29] P. Werner, A. Al-Hamadi, K. Limbrecht-Ecklundt, S. Walter, S. Gruss, and H. C. Traue, ‘‘Automatic pain assessment with facial activity descriptors,’’ IEEE Trans. Affect. Comput., vol. 8, no. 3, pp. 286–299, Jul./Sep. 2017.

[30] K. N. Phan, S.-H. Kim, H.-J. Yang, and G.-S. Lee, ‘‘Multimodal convolutional neural network model for protective behavior detection based on body movement data,’’ in Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW), Sep. 2021, pp. 01–06.

[31] G. Dray, P.-A. Jean, J. Montmain, and N. Sutton-Charani, ‘‘The AffectMove challenge: Some machine learning approaches,’’ in Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW), Sep. 2021, pp. 1–5.

[32] V. D’Amato, L. Oneto, and D. Anguita, ‘‘Keep it simple: Handcrafting feature and tuning random forests and XGBoost to face the affective movement recognition challenge 2021,’ Comput. Intell. Interact. Workshops Demos (ACIIW), Sep. 2021, pp. 1–7.

[33] K. Radouane, A. Tchechmedjiev, B. Xu, and S. Harispe, ‘‘Comparison of deep learning approaches for protective behaviour detection under class imbalance from MoCap and EMG data,’’ in Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW), Sep. 2021, pp. 1–8.