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Article

Future perspectives on artificial intelligence-driven translation and standardization of English biosensor terminology across cultures

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Abstract: Standardized English language and efficient translation techniques are required to guarantee global usability and cultural relevance because of the growing dependence on biosensors in communication technologies. In particular, the research aims to understand the role of biosensors, particularly wearable sensors, in enabling communication in other cultures, like using a sign language (SL) translator system. The information would be recorded through motion sensors designed to determine hand movements and gestures based on any recorded movement. Raw data would need bandpass filtering of both extraneous artifacts and the surrounding noise. Visual Geometry Group 16 (VGG16) is applied for feature extraction from biosensor data. A novel Adjustable Moth Flame-Tuned Efficient Recurrent Neural Network (AMF-ERNN) transformer model that is used to achieve translations from sensor signals to text sentences is introduced. AMF is used to select and optimize the features of an ERNN model to enhance its efficiency and performance while translating sensor signals to text. Results show that the suggested model outperformed traditional algorithms by achieving accuracy (98.5%), recall (98.3%), precision (98.2%), F1-score (98.4%), and WER (35.5%). These results demonstrate the way biosensors can promote accurate and culturally aware translations. The study concludes by emphasizing the importance of English terminology standardization to enhance the accessibility and effectiveness of biosensor-based translation systems across diverse cultural contexts.

Keywords: English terminology; translation strategies; biosensors; cross-cultural; adjustable moth flame tuned-efficient recurrent neural network (AMF-ERNN)

1. Introduction

In an increasingly connected world, cross-cultural knowledge exchange in science is what furthers research, innovation, and global collaborations. This is especially true when taking into consideration the multi-disciplinary domain of biosensors, the incorporation of chemistry, biology, physics, and engineering to make it possible to develop a sensing device that can recognize the presence of biological molecules by converting them into a detectable signal [1]. However, the importance of invention is that as biosensor technology matures and diversifies into various forms beyond healthcare diagnostics towards environmental monitoring and food safety, proper standardization of terminology applied becomes very important to ensure clear usage. It has to do with the establishment of standard use of English terminology as well as proper translation tactics in terms of cross-cultural communication [2]. Language is the communication tool through which knowledge can be shared. However, the variations in languages and cultures easily present obstacles to the propagation of technical-scientific knowledge to the rest of the globe [3]. While scientific and technological language has become the lingua franca through English, it does not promote non-English speaking professionals as much [4]. The terminologies that accompany biosensor research are naturally found in the English language, and understanding and participating in this area therefore remain difficult for most natural speakers. Misinterpretation of terms, inconsistent translations, and lack of standardized definitions can lead to confusion, errors, and even the misapplication of biosensor technologies [5].

Therefore, it has resulted in an increased need to standardize the terminology involved in biosensors, since it is a highly expanding field with vast applications in various industries. Biosensors are applied in disease diagnostics, pathogen detection, monitoring glucose concentration, and assessment of environmental pollutants, among other things [6]. Each of the applications necessitates the use of accurate terms that describe the parts of the biosensor, the mechanism of working, and its outputs. For example, the use of the term's transducer, analyte, and bioreceptor needs to be clearly understood around the world for the proper collaboration of researchers, manufacturers, and end-users of different countries [7]. The translation strategies also help bridge the linguistic gap and ensure that the meaning is preserved from one language to another for technical terms. This involves not only literal translation but also adaptation of concepts in light of the cultural and linguistic contexts of the target audiences. Some technical terms do not have direct equivalents in some languages, this makes the translators use descriptive phrases or even invent new terms. This is called neologism and should be taken with care lest it deviates from consistency and proliferates, as many terms for the same [8].

From a cross-cultural viewpoint, standardization and translation pose questions about equity and inclusiveness. The dominance of the English language in scientific communication creates hierarchies of knowledge by devaluing or completely overlooking contributions from non-English-speaking researchers [9]. Standardized terminology and good translation strategies can be developed to foster a more inclusive environment in the world scientific community that will appreciate diverse perspectives and contributions [10]. Cultural factors may influence the perception and understanding of some biosensor concepts. For instance, the cultural aspect of health and disease could mean the application and reporting of biosensors differ regionally. In such cases, standardized terminology ensures the technical aspects of the biosensor allow variability in terms of cultural nuances with translation strategies [11].

1.1. Aim of the research

The objective is to explore the use of biosensors, specifically wearable sensors, in improving cross-cultural communication, especially in the improvement of a sign language (SL) translation system. A new Adjustable Moth Flame-Tuned Efficient Recurrent Neural Network (AMF-ERNN) technique is to optimize sensor data translation for improved accuracy, efficiency, and cultural relevance in translating sensor signals into text.

1.2. Key contribution

- To introduce a novel Adjustable Moth Flame-Tuned Efficient Recurrent Neural Network (AMF-ERNN) model for sensor signal translation.
- To apply bandpass filtering for pre-processing and VGG16 for feature extraction from biosensor data.

- To emphasize the importance of standardized English terminology for enhancing the global accessibility of biosensor-based translation systems.

2. Related work

D'Alton et al. [12] discussed the key aspects of the biosensor translation process, such as choosing analytical biomarkers, carrying out clinical trials, gaining regulatory permission, interacting with consumers, developing manufacturing and scaling-up plans, health economics, and legal and ethical issues. Clinical choices could be greatly aided by Point-of-care (POC) biosensors, particularly in remote and underprivileged settings. Although there were a limited number of commercial biosensors available due to extensive research, the translation of these biosensors into commercial goods was expanding quickly.

A Many-to-Many multilingual translation model able to translate between any two hundred languages was created by Fan et al. [13]. The training data set used by the model covers thousands of language directions and was produced by dense scaling and large-scale mining. The focus was on non-English-centric models, which translate across non-English directions with gains of more than 10 BLEU. The model's performance was comparable to that of the top single systems from the workshop on machine translation.

Zai [14] explored the adaptation of biosensing technologies for vocabulary teaching in Spanish. The knowledge and understanding gaps of students could be detected by tracking physiological signals through biosensors. It brought new concepts and ways to use biosensing technology in teaching languages, which could change conventional teaching methods and improve the output of Spanish language training.

Saquib and Rahman [15] developed a system to recognize fingerspelling through sensors by the use of gloves of Bengali Sign Language or BSL and American Sign Language (ASL). The system could detect both symbols in the alphabet, with possible accuracy. Its methodology was very suitable to be implemented in resource-constrained environments, providing a unique approach towards the continuous symbol assessment from the run-time data. It was one of the valuable methods developed for the hearing impaired and the mute people relying on their hand gestures to communicate themselves.

Lee et al. [16] has developed a wearable, intelligent system for interpreting utilizing deep learning (DL) and sensor fusion. The system recognized dynamic ASL motions with an average accuracy of 99.81%. The system advances communication and the quality of life for hard-of-hearing persons.

Zhou et al. [17] used a machine learning (ML)-supported wearable sign-to-speech device. It could convert ASL hand motions into speech with good reliability. The high sensitivity and quick response of the system make real-time translation possible. With 660 learned SL hand gesture recognition prototypes, the identification rate of the system was found to be 98.63% and the recognition time of the system was less than one second.

Calado et al. [18] proposed an electronic-based wearable setup for automatic, signer-independent Italian SL recognition. The device applies six inertial measurement units (IMUs) and a sensory glove to measure gestures with the hands, arms, and forearms. The system removes three IMUs, reducing complexity and ensuring accurate categorization, which gives an accuracy of 93.91%. The signer-independent method adds realism to the application.

Padmanandam et al. [19] proposed a wearable surface electromyography (EMG) biosensing device on the base of Deep SLR and an SL recognition system to enhance communication for the deaf. The device translates SL into audio or printed messages, making hand gestures easier to understand. The gadget had a recognition time of less than 0.9 s and an average word mistake rate of 9.6% while being tested on iOS and Android handsets.

DelPreto et al. [20] suggested a wearable gadget that builds a network of resistive sensors using conductive knit. It was linked to a low-profile microcontroller that has ML and an accelerometer. In real-time, the device could recognize both dynamic movements and static positions in ASL. Twelve ASL characters and words can be recognized by the glove and microcontroller. Networks could correctly roll predictions and identify 96.3% of segmented samples.

Erdem et al. [21] suggested that wearable sensor technologies are growing in prominence in biomedical and hospitals for their practical uses. The biosensors have used such as disease detection and diagnosis, treatment, monitoring patients, and overall wellness administration. The incorporation of sensors into recent technologies made the performance of the framework very effective.

Voyvodic and Bonnet [22] examined the biosensor's customized applications in medicine by allowing rapid and accurate identification of biochemical signals for themselves. Modern biosensors integrate nanomaterials and intelligent algorithms for better responsiveness and instantaneous evaluation. Portable biosensors, such as smartwatches provide continuous monitoring of health and advocate earlier intervention.

Research gap

Current biosensor-based translation systems face challenges in accurately converting sensor data into text, particularly in cross-cultural contexts. Issues include limited language diversity, inadequate standardization of terminology, and difficulties in optimizing sensor data for real-time applications. Existing models lack cultural sensitivity and struggle with non-English languages. To address these challenges a novel AMF-ERNN model is suggested. Advanced Artificial intelligence (AI) techniques optimize sensor data processing and translate accuracy, efficiency, and relevance for cultures. This solution enables the production of real-time standard translation and supports diversity in linguistic and cultural settings to make it accessible and inclusive.

3. Methodology

This section introduces the relevant methodologies applied in the proposed research, which include the usage of sign language MNIST dataset for gesture recognition and a bandpass filter applied to preprocess data from biosensors, an implementation of VGG16 to extract features for recognizing gestures, and the adoption of the novel AMF-ERNN method towards maximizing sensor data translation efficiency. All these methodologies are relevant to the accurate and efficient translation of SL. **Figure 1** displays the overall process flow of the recommended model.

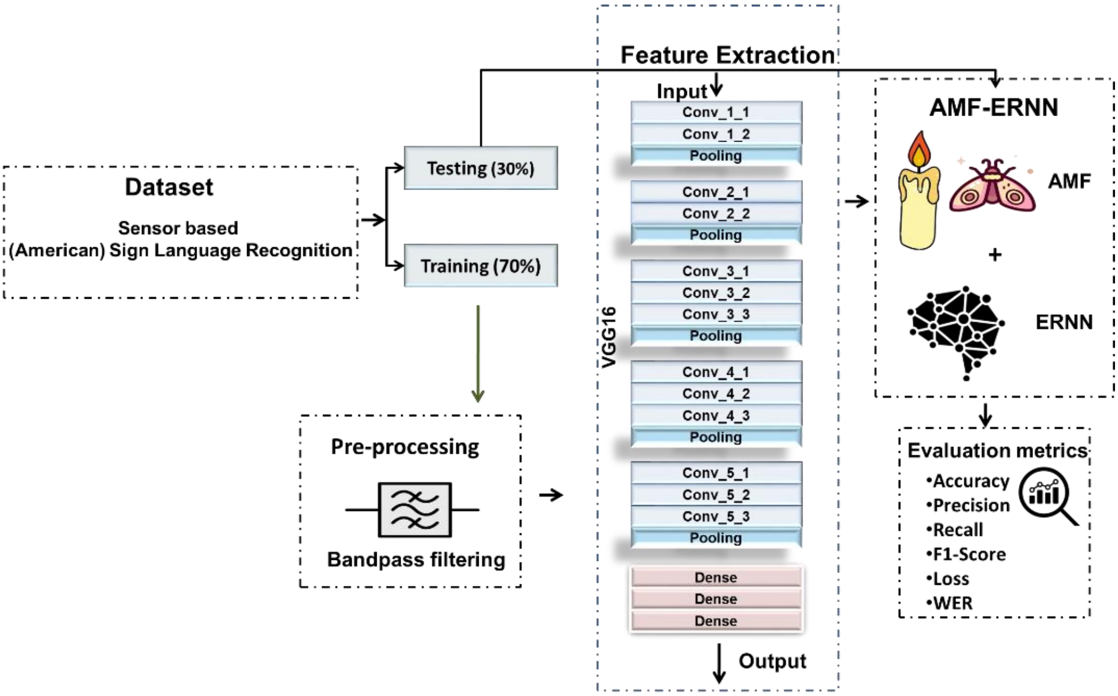


Figure 1. Methodology flow of AMF-ERNN model.

3.1. Dataset

The Sensor-Based American Sign Language Recognition Dataset on Kaggle [23] includes data collected using wearable sensors. This dataset features sensor data from smart gloves designed to translate SL into spoken language. Each glove is equipped with five flex sensors and a Grove 6-axis Accelerometer and Gyroscope per hand, enabling detailed measurement of hand movements and gestures. The dataset consists of recordings from multiple individuals, with each entry representing a sequence of 20 frames. For each hand, three types of measurements are captured: Flexion, which measures the degree of finger bending for all five fingers; acceleration, detailing movement in 3D space across X, Y, and Z axes; and orientation, describing the hand's 3D positioning in space. This results in 11 measurements per hand per frame, totaling 440 columns when aggregated over 20 frames for both hands. A target column labeled SIGN identifies the specific sign language gesture for each sequence, making this dataset highly suitable for ML tasks focused on gesture recognition and translation. The dataset is split into 70% for training and 30% for testing, providing a robust framework for developing and evaluating machine learning models focused on gesture recognition and translation.

3.2. Bandpass filtering

In the context of biosensor data, bandpass filtering is an important pre-processing step to remove noise and unwanted artifacts from raw sensor signals, such as those from EMG or motion sensors. Digital bandpass filtering would be applied to isolate frequency bands that contain the most relevant information for gesture recognition and sign language translation. The center frequency and bandwidth of the filter shall be chosen carefully to eliminate noise and all irrelevant signal components while allowing the critical features related to hand gestures. After using the bandpass filter, the filtered data is subjected to further processing using various feature extraction techniques, such as Visual Geometry Group 16 (VGG16).

This pre-processing approach proves highly appropriate for biosensor data in enhancing signal quality, therefore, it filters off noises allows for clearer extraction of features, and later trains the model for this recognition task. It lets the sensor signals retain all information relevant to further processes.

3.3. Feature extraction using visual geometry group 16 (VGG16)

In the context of gesture recognition and sign language translation, the VGG16 (**Figure 2**) model is used for feature extraction from biosensor data, especially from images of hand gestures. VGG16 is a widely used DL architecture, well-suited for classification tasks because it can capture spatial hierarchies and intricate patterns within visual data. A structure that will be used in the proposed work is the VGG16, whose network layers will extract meaningful features for the input of images of hand gestures after filtering, starting from bandpass filtering. Architecture VGG16 comprises pooling layers, convolutional layers, and fully connected layers combined to learn the complex input data features. The network has 16 layers, and 3 × 3 filters are functional to the input image, which is resized to 224 × 224 pixels. This architecture ensures the model is highly accurate in distinguishing and classifying different hand gestures. The final stage of this output layer provides class probability using an activation function for all the gestures to be classified exactly. Using VGG16 power features, it efficiently converts the hand gestures to text with high effectiveness in the sign language translation application.

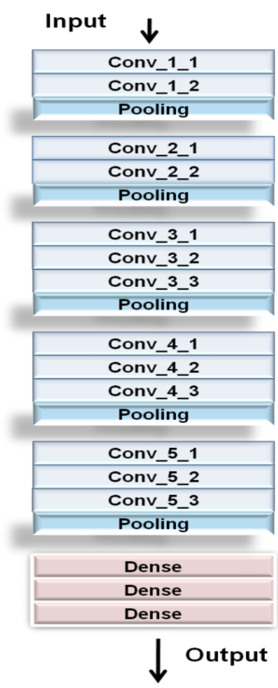


Figure 2. Structure of VGG16 for extracting features.

VGG16 is particularly apt for the task because it has an excellent robust capability to mine detailed features from images so that accurate gesture recognition within SL translation systems becomes possible. Deep architecture helps in more differentiation between minute differences in the hand gestures of the translators.

3.4. Proposed method AMF-ERNN

AMF-ERNN combines the optimization ability of the AMF algorithm with the ERNN to produce a superior performance structure in complex tasks, such as gesture recognition and optimization.AMF-ERNN is a hybrid approach that incorporates the AMF optimization algorithm with an ERNN. The adaptive search strategy in AMF improves global and local exploration by balancing exploration and exploitation, while the advanced learning structure of ERNN is helpful for effective sequence modeling and pattern recognition.

3.4.1. Efficient recurrent neural network (ERNN)

The ERNN excels in dynamic prediction by leveraging the adaptive and recurrent feedback it has. The ERNN catches the temporal dependencies and the spatial correlations in an efficient way. AMF-based optimization of this model ensures robust and accurate adaptable performance for real-time applications. There are two fundamental parts to the designed ERNN predictor: Network parameter optimization using the AMF approach and the design of adaptive RNN, which will be dealt with in the discussions as follows.

The architecture of the ERNN model

Figure 3 graphically depicts the network topology of the suggested ERNN predictor. Direct, adaptive, and recursive predictions are all combined in the ERNN predictor. A multi-layer feed-forward NN with adaptive and recurrent feedback links from user-selected nodes is used in its construction. This flexibility allows users to easily adjust the connection topology based on the specific gesture recognition application. While the recurrent feedback connections handle temporal dependencies, the adaptive feedback connections effectively capture spatial-temporal information. The network can memorize the information from previous time steps, which aids in predicting the current state of the hand gestures, which store previous gesture states for contextual processing. **Figure 3** represents the network architecture of the ERNN model.

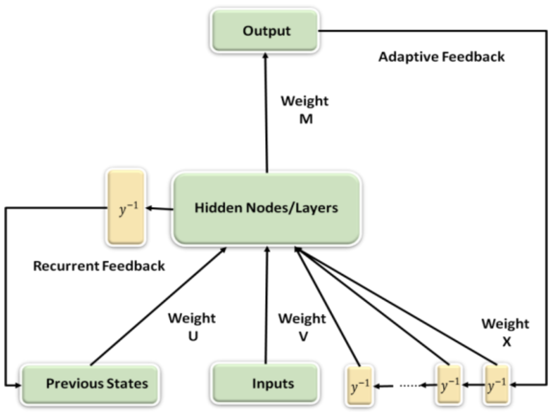


Figure 3. ERNN predictor's network architecture.

Nodes in the output layer of the created ERNN predictor utilize linear activation functions (AF), whereas nodes in the hidden layers use sigmoid AF. Accordingly, depending on the type of sigmoid AFs used, the inputs $w_j(m)$ prior condition from the hidden layers $z_g(m–1)$ and the prior outputs $z_p(m-l)$ appropriately normalized. The output of the first hidden layer's i-th node for the m th sample is provided in Equations (1) and (2).

$$z_i(m) = e(net_i) \tag{1}$$

$$net_i(m) = \sum_g v_{ig} z_g\,(m-1) + \sum_k x_{ik}\, z_p(m-k) + \sum_j u_{ji} w_j(m) + \theta_i \tag{2}$$

where V, U, and X are the system weight matrix that represents the prior states, inputs, and outputs, correspondingly; where θ_i is the bias; $k = 1, 2, \dots, K$, in which K, is the maximum output feedback depth; the selected AF is $e(.)$. Any type of multi-layer perceptron (MLP) can be utilized to connect the first hidden layer to the network output (Equation (3)).

$$z_p(m) = h(z(m)) \tag{3}$$

where h (.) represents the MLP's nonlinear mapping. The inclusion of temporal features through the state-adaptive and recurrent feedback ensures that past information from previous stages is effectively utilized to improve the prediction of the current and future hand gesture states, enabling more accurate gesture recognition for translation applications.

The ERNN network training

For the ERNN predictor created to produce the best input/output mapping, for gesture recognition, it must be appropriately trained. Representative training data covering all potential application scenarios must be used for offline training. Since the majority of real-world gesture recognition systems function in noisy and/or unpredictable environments, it is challenging to meet these criteria in real-world applications. Classical forecasting approaches typically assume time-invariant systems or arrangements with slowly changing parameters. The dynamic properties of gesture recognition systems may abruptly change due to factors like sudden environmental changes or system recalibration. To adapt the ERNN weights to time-varying system conditions, an AMF approach is used in this section.

$\left\{w^{(m)} z_c^{(m)}\right\}^S$, where $w^{(m)}$ is a vector containing the inputs together with the earlier gesture condition and output; $m = 1, 2, \dots, M$; M is the whole quantity of preparation data sets; and $z_c^{(m)}$ is the intended result. For each of the N training data sets, the goal function is specified as Equation (4).

$$F = \frac{1}{2} \sum_{M=1}^{M} \lambda^{M-m} \left(z_p^{(m)} - z_p^{(m)}\right)^2 = \frac{1}{2} \sum_{M=1}^{M} \lambda^{M-m}\, \varepsilon(m, \Theta)^2 \tag{4}$$

where the forgetting factor is the $\lambda \in (0\ 1)$, $\lambda \in (0.9\ 1)$is typically employed to prevent potential convergence unsteadiness; all the network weights $\Theta \in R^{r\times 1}$; the point forecasting error is εand V1 represents all of the network weights. To avoid directly inverting the Hessian matrix in this situation, one solution is to use the matrix inversion lemma. One diagonal constituent is inserted at a time rather than the $r \times r$matrix $\mu(m)J$ at each step. Consequently, the ERNN's weights are updated recursively by Equations (5) and (6).

$$\hat{\Theta}(m) = \hat{\Theta}(m-1) - Q(m-1)\varphi\left(m, \hat{\Theta}(m-1)\right)^S \varepsilon(m, \hat{\Theta}(m-1)) \tag{5}$$

$$Q(m) = \frac{1}{\lambda}\Big\{ Q(m-1) - Q(m-1)\varphi^*(m, \hat{\Theta}(m-1))^S \left[\lambda \Lambda^{*^{-1}} + \varphi^*\left(m, \hat{\Theta}(m-1)\right) Q(m-1)\varphi^*(m, \hat{\Theta}(m-1))^S\right]^{-1} \varphi^*\left(\hat{\Theta}(m-1)\right) Q(m-1)\Big\} \tag{6}$$

$\hat{\Theta}(m)$is the estimate of sample moment m; $\varphi = c\varepsilon / c\Theta$ is the Jacobian matrix; Q is an estimated Hessian matrix's inverse; and $Q(0)$ is selected as an identity matrix $\alpha_M J$ with constant $\alpha_M \epsilon [10^3 10^5]$; φ^* are, respectively in Equations (7) and (8).

$$\varphi^*(m, \Theta^{\wedge}\ (m-1))^S = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \varphi(m, \hat{\Theta}\ (m-1))^S \quad 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} position\ m\ (mod\ r) + 1 \tag{7}$$

$$\Lambda^*(m) = \begin{bmatrix} 1 & 0 \\ 0 & r\mu(m) \end{bmatrix} \tag{8}$$

The trust region radius is impacted by the AMF parameter n, and it should be adaptively adjusted in response to the updated weights' performance. It employs the subsequent approach: Setting the starting value $\mu(1)$ to 0.1, reduce $\mu(m)$ by $\mu(m)/l$ if the objective function (OF) in Equation (4) drops when the weights are rationalized; if the OF enhances as the weights are modernized, expand $\mu(m)$ by $l\mu(m)$, where l is a design parameter. Several simulation studies have been carried out to ascertain the parameters in terms of convergence speed and training correctness. $\mu(1)$ = 0.1 is utilized as an initial value that will be modified throughout training after $\mu(1)$ = [0.01, 1] has been tested. However, $l \in$ [1.01, 2.00] was investigated in this work; a lesser value of k slows down the training process, while a bigger value of l may cause training instability. In this work, l = 1.15 is utilized.

3.4.2. Adjustable moth flame (AMF)

The AMF algorithm is highly suitable for objective as it enhances exploration and exploitation balance through adaptive position updates and population diversity. Incorporating orthogonal opposition-based learning (OOBL) strategy and hybrid search mechanisms improves convergence speed and global optimization, making it ideal for complex, high-dimensional problems like gesture recognition or optimization tasks.

Purpose of refining MF algorithm

The population-based optimization technique known as MF, is based on the flight patterns of moths. It balances the performance of exploitation and exploration by enabling rapid information flow between flames and moths. However, the best people from the present iterative flames and moths generate flames, and MF occasionally suffers from a lack of diversity. Rapid information interchange is possible with this approach, but flame variety may be lost. The adaptive guiding moth position update system can enhance local search capabilities and decrease the amount of flames. The AMF algorithm, which incorporates AMF techniques, is recommended as a solution to these problems.

Ignition generation with orthogonal opposition-based learning (OOBL) strategy

The AMF incorporates the OOBL approach, which unites Orthogonal Experiment Design (OED) and Opposition-Based Learning (OBL) to overcome dimensional degradation issues in reverse solutions. In the context of enhancing gesture recognition for sign language translation, the OOBL mechanism ensures diversity in the population and strengthens both the exploration and exploitation capabilities of the algorithm. $E_j = \left[e_{j1}, e_{j2}, \dots, e_{jc}\right]$ and its independent reverse $\check{E}_j = \left[\check{E}_{j1}, \check{E}_{j2}, \dots, \check{E}_{jc}\right]$ and orthogonal cannot be used directly since individual dimension d is typically bigger than factor L (Equations (9) and (10)).

$$\begin{cases} E_{j1} = [e_{j1}, e_{j2}, \dots, e_{jq_1}] \\ E_{j2} = [e_{jq_1+1}, e_{jq_2+2}, \dots, e_{jq_2}] \\ \cdots \\ E_{jL} = [e_{jq_L+1}, e_{jq_L}, \dots, e_{jc}] \end{cases} \tag{9}$$

$$E_j = \left[E_{j1} E_{j2} \cdots E_{jL}\right] \tag{10}$$

$$1 \le q_1 < q_2 < \cdots < q_{L-1} \le c.$$

The best and worst flames are chosen to create the OOBL flames to increase population variety and the MF algorithm's capacity for exploration. The following is the OOBL flames FM (Equations (11)–(13)).

$$E_{bestnew} = lb_{best} \times ones(1, c) + (ub_{best} \times ones(1, c) - E_{best}) \tag{11}$$

$$E_{worstnew} = lb_{worst} \times ones(1, c) + rand(lb_{worst} \times ones(1, c) - E_{worst}) \tag{12}$$

$$EN = [E_{bestnew}; E_{worstnew}] \tag{13}$$

The worst flame and optimal flame are represented by E_{worst} and E_{best}, while the OOBL explanation of the worst flame and the optimal flame are represented by $E_{worstnew}$ and $E_{bestnew}$. Random number in [0,1] that is preferred to enlarge arbitrariness and the likelihood of bound away of the local optimum; ub_{best}, lb_{worst}, ub_{worst}, and lb_{worst} symbolize the lower and upper limits of the worst flame and the optimal flame.

Adjusted moth position shift algorithm

The proposed hybrid investigates approach and mutation operator-based adjusted position update method for moths is proposed to enhance the global search capability and convergence speed of the MF algorithm. The adjusted location update mechanism is divided into two halves, with the mutation operator improving global search ability and spiral. The maximum Euclidean distance is calculated in the following Equations(14) and (15).

$$C_F = \sqrt{\sum_{i=1}^{c} \times (ub_i - lb_i)^2} \tag{14}$$

$$c_j = \sqrt{\sum_{i=1}^{c} \times (N_{ji} - E_{best\ i})^2} \tag{15}$$

The following describes how moths' modified position update system works:

- When $c_j \leq x.C_F$ in the iterative search process, a linear search mechanism is implemented. Equations (16) and (17) is the most recent position of moths.

$$N_j(k+1) = \begin{cases} N_j - B.C_j', & j \leq e_{no} \\ C_j \times f^{as} \times cos(2\pi s) + E_{e_{no}}(k) & j > no \end{cases} \tag{16}$$

$$\begin{aligned} C_j' &= |D.E_j - N_j| \\ C_j &= |E_{e_{no}} - M_j \end{aligned} \tag{17}$$

where the value is 0.1 and x is the weight coefficient; $B = 2b \cdot Q - b$; $D = 2 \cdot Q$; $b = -1 + l \times \left(-\frac{1}{K}\right)$; changing the values of B and D. one may go to different locations around the flame about the present position.

- To increase population diversity, the iterative search method updates the moth position using a mutation operator when $c_j > x \cdot C_F$. The operator for mutation is described in Equation (18).

$$N_j(k+1) = N_{h1}(k) + Q_n \otimes (N_{h2(k)} - N_{h3(k)}) \tag{18}$$

With h_1, h_2, and h_3 being random values that are not equal to j in $[1, m]$, and N_{h1}, N_{h2} and N_{h3}being randomly chosen from N. Random position vector $Q_n = [r_1, r_2, \dots, r_c]$ and uniformly distributed random integer $r_i(i = 1, 2, \cdots, c)$in [0, 1] are both represented by $\otimes$. The AMF algorithm's pseudo code is displayed in Algorithm 1.

Algorithm 1 AMF

1: Initialize each person in moths at random.
2: Initialize the iteration count $k = 1$;
3: While $k < L + 1$
4: Update e_{no} using (10);
5: $OM = Fitness\ Function\ (N)$;
6: If $k == 1$
7: $e = sort\ (N)$; $OF = sort(OM)$;
8: Select the $optimum\ E_{best}$ and E_{worst};

Algorithm 1 (*Continued*)

Else
  $e = sort(N(k-1), N(k), FM)$; $OF = sort\ (OM(k-1), OM(k), OFM)$;
  end If
Select the best m individuals to form the flame population;
 for $j = 1{:}m$
  If $c_j \leq x.C_F$
  for $i = i{:}c$
    Update q, s, B and D;
Calculate C and C' $using$ (21);
     Update $N_{j,i}$ using (22);
     end for
    end If
    If $c_j > x.\ C_F$
      Update $N_{j,i}$ using (22);
    end If
  end for
FM ID obtained by OOBL of E_{best} and E_{worst};
  $OFM = Fitness\ Function\ (FM)$;
Update the best solution E_{best};
$k = k + 1$;
end while

This combination of two techniques helps AMF-ERNN optimize complex tasks more effectively, especially in dynamic environments like gesture recognition, where the exploration of diverse solutions as well as learning from sequential data is important for achieving better performance and accuracy. The pseudocode for the proposed method is provided in Algorithm 2.

Algorithm 2 AMF-ERNN

$class\ ERNN$:
  $def\ \_\_init\_\_(self, input\_size, hidden\_size, output\_size)$:
    $self.weights\ =\ initialize\_weights(input\_size, hidden\_size, output\_size)$
  $def\ forward(self, X)$:
    $return\ output\_layer\_activation(rnn\_layer\_activation(X, self.weights))$
  $def\ loss(self, predicted, actual)$:
    $return\ mean\_squared\_error(predicted, actual)$
$Class\ AMF\ Optimizer$:
  $def\ \_\_init\_\_(self, pop\_size, max\_iter)$:
    $self.pop\_size, self.max\_iter\ =\ pop\_size, max\_iter$
    $self.moths\ =\ initialize\_population(pop\_size)$
  $def\ optimize(self, model, X\_train, y\_train)$:
    $for\ \_\ in\ range(self.max\_iter)$:
      $fitness\ =\ [1\ /\ (1\ +\ model.loss(model.forward(X\_train), y\_train))\ for\ moth\ in\ self.moths]$
      $sorted\_moths\ =\ sorted(zip(self.moths, fitness), key = lambda\ x{:}\ x[1], reverse = True)$
      $best, worst\ =\ sorted\_moths[0][0], sorted\_moths[-1][0]$
      $For\ a\ moth\ in\ self.moths$:
        $distance\ =\ euclidean\_distance(moth['position'], best['position'])$
        $moth['position']\ =\ update\_position\_best(moth, best)\ if\ distance\ <$
  $some\_threshold\ else\ update\_position\_mutation(moth, worst)$

Algorithm 2 (*Continued*)

```
        return model.weights
# Initialize and optimize
model = ERNN(input_size = 10, hidden_size = 50, output_size = 1)
optimizer = AMFOptimizer(pop_size = 30, max _iter = 100)
model.weights = optimizer.optimize(model, X_train, y_train)
# Test optimized model
test_predictions = model.forward(X_test)
```

4. Experimental result

This section details the experimental setup, describing the methodologies, configurations, and data used for evaluation. It also highlights the key evaluation metrics, contrasting the performance of the suggested approach with existing models through a comprehensive analysis of multiple performance indicators.

4.1. Experimental setup

The system was equipped with a Graphics Board (GB) capable of handling intensive computations, specifically a GPU with at least 8 GB of VRAM to speed up the training process for the ERNN. Primary libraries used for the experiment included TensorFlow 2.0 for neural network modeling and training in Python, NumPy for numerical operations, and SciPy for optimization tasks. The hyperparameter setting is found in **Table 1**.

Table 1. Hyperparameter setting.

Hyperparameter	**Range/Value**
Learning Rate (α)	[0.01, 0.1]
Forget Factor (λ)	[0.9, 1.0]
Initial (μ)	0.1
Mutation Factor (l)	1.15
Number of Layers	3
Number of Units per Layer	50–100
AF	Sigmoid (hidden), Linear (output)
Maximum Output Feedback Depth (K)	5
Population Size (P)	50

4.2. Evaluation parameters

4.2.1. Accuracy

It estimates the overall accuracy of the technique by evaluating the ratio between the correct calculation and the whole predictions, as shown in Equation (19) (TP-True positive; TN-True negative; FP-False positive; FN-False negative).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{19}$$

4.2.2. Precision

It refers to the quality of predictions, and Equation (20) measures the ratio between true predictions and all predicted positive forecasts.

$$Precision = \frac{TP}{TP + FP} \tag{20}$$

4.2.3. Recall

It is also known as sensitivity. The capacity of the model to identify all information in a relevant class. Divide the whole numeral of positive results by the whole numeral of false negatives to determine the recall, as shown in Equation (21).

$$Recall = \frac{TP}{TP + FN} \tag{21}$$

4.2.4. F1-score

To identify class-imbalanced datasets, the F1-score is superior to accuracy. The F1-score occurs in the actual values of precision and recall when they are similar in value. It appears to be the lower of the two metrics when recall and precision are widely distant, as shown in Equation (22).

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{22}$$

4.2.5. Word error rate (WER)

It is used to assess how similar two sentences are in the WER. This measurement counts the smallest number of substitution (S), deletion (D), and insertion (I) operations for each generated sentence that is compared to the ground truth sentence. After that, it indicates the number of words in the ground fact statement as G, and Equation (23) can be used to get the WER. A lower WER indicates that the translation process is more accurate.

$$WER = \frac{S + D + I}{G} \times 100\% \tag{23}$$

4.2.6. Accuracy and loss

When represented as a percentage, accuracy is the proportion of accurate forecasts to all predictions. In the loss, which adds all the mistakes made for every sample in training or validation sets, is the dissimilaritybetween the expected and the actual target valueis measured. It is common practice to evaluate a method’s learning act using both accuracy and loss. There is no mathematical connection between accuracy and loss, even though they are frequently related and that accuracy rises as loss falls.

4.3. Comparison phase

Table 2 contrasts the performance of the suggested AMF-ERNN form with existing models, GRU-LSTM [24] and LSTM-GRU [24] in conditions of recall, precision, and F1-score.

Table 2. Proposed method comparison.

Method	Recall (%)	Precision (%)	F1-score (%)
GRU-LSTM [24]	89	91	89
LSTM-GRU [24]	97	97	97
AMF-ERNN [Proposed]	98.3	98.2	98.4

Figure 4 comparing precision highlights the effectiveness of the proposed AMF-ERNN model against existing methods. The proposed model achieved a precision of 98.2%, outperforming GRU-LSTM (91%) and LSTM-GRU (97%). This demonstrates the AMF-ERNN model's superior ability to accurately identify relevant outputs, reducing false positives in the translation of biosensor data to text. The results validate the enhanced feature optimization and processing capabilities of the AMF-ERNN model.

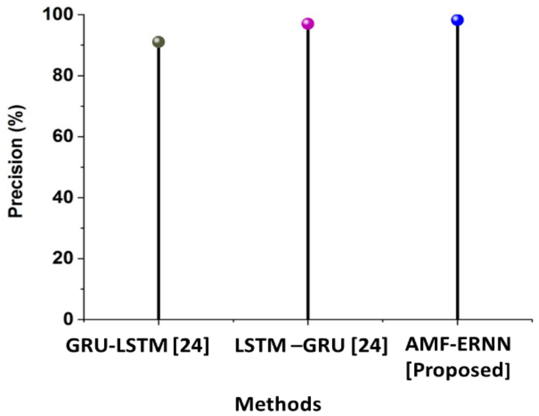


Figure 4. Precision comparison of AMF-ERNN over existing approaches.

The recall comparison (**Figure 5**) shows that the proposed model can capture all relevant instances with high accuracy. AMF-ERNN achieved a recall of 98.3%, significantly higher than the GRU-LSTM model (89%) and slightly better than the LSTM-GRU model (97%). This suggests that the AMF-ERNN model is highly effective in minimizing false negatives, ensuring that all relevant data for translation tasks are identified, and making it very reliable for cross-cultural communication.

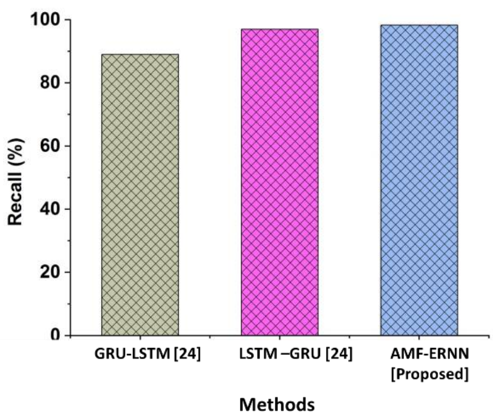


Figure 5. AMF-ERNN recall comparison with traditional approaches.

The F1-score (**Figure 6**) combines recall and precision to evaluate the overall performance of the methods. The proposed AMF-ERNN model achieved the highest F1-score at 98.4%, surpassing GRU-LSTM (89%) and LSTM-GRU (97%). This confirms the balanced and robust performance of the AMF-ERNN in translating biosensor signals to text with both high accuracy and recall, marking a significant improvement over existing methods in biosensor translation tasks.

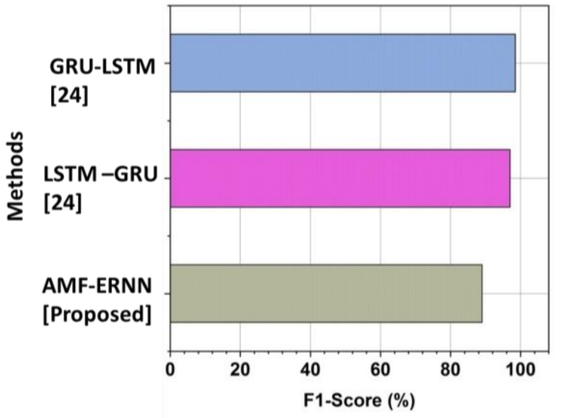


Figure 6. F1-score performance of AMF-ERNN vs. traditional models.

4.4. Output of proposed method

Table 3 shows the accuracy of the suggested AMF-ERNN. This model was able to interpret the biosensor data into text with an accuracy of 98.5%. The WER was recorded at 35.5%, showing a relatively low error rate in translating sensor signals into text. The accuracy in **Figure 7** underscores the model's high performance in making accurate identifications and properly translating relevant data within their appropriate contexts. WER gives a measure of translation quality concerning room for improvement in minimizing translations. **Figure 7** gives the graphical representation of accuracy and WER.

Table 3. Accuracy performance of the proposed method.

Method	Accuracy	WER
AMF-ERNN [Proposed]	98.5%	35.5%

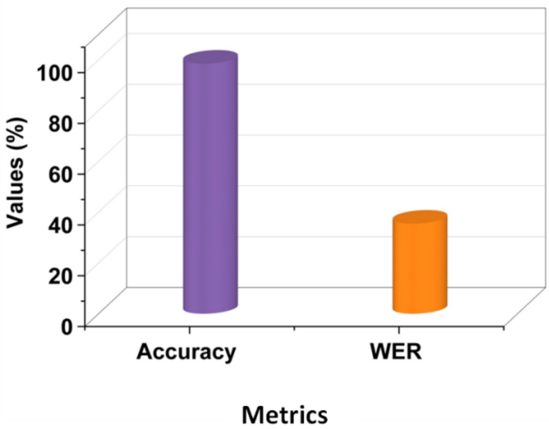
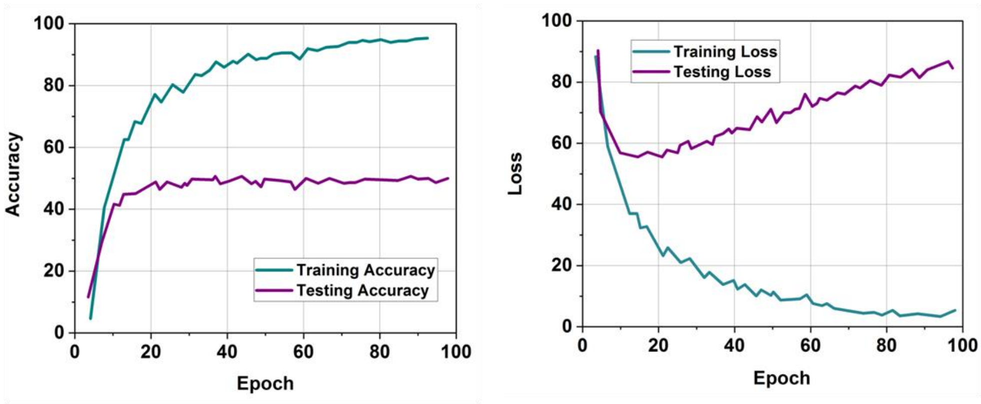


Figure 7. Accuracy and WER graph of proposed AMF-ERNN method.

Figure 8 demonstrates model performance over time during training. This shows both accuracy and loss on a graph. From the graph, the accuracy appears to be increasing, indicating that the model predicts results more accurately as the training time progresses. The loss will continue to decrease, showing less discrepancy between the predicted and actual values, indicating that the model is improving its learning ability and minimizing errors. This graph makes it clear to view the model's learning trajectory as the training advances in effectiveness at both accuracy improvement and loss reduction.



(a) **(b)**

Figure 8. Graph of AMF-ERNN method: **(a)** Accuracy; **(b)** loss

5. Discussion

The comparison phase demonstrates the significant performance improvements of the proposed AMF-ERNN model over existing methods, including GRU-LSTM and LSTM-GRU. While the existing methods are effective in certain applications, they suffer from the limitations related to feature optimization and the balance between precision and recall. GRU-LSTM tends to suffer from lower recall missing some relevant instances in biosensor translation tasks. Although computationally advantageous, it was unable to precisely combine both short- and long-term interactions, which may result in decreased precision for complicated data sets. Similarly, LSTM-GRU could be more effective in handling and maintaining long-term dependencies, but it frequently failed to demonstrate the capacity for adaptation needed to optimize characteristics specific to the domain operations such as multilingual adaptation of biosensor terminologies. In contrast, the recommended AMF-ERNN model addresses these problems with the AMF optimization algorithm, with real-time fine-tuning of feature selection that ensures the framework is adapted properly to the distinct cultural and linguistic unique characteristics observed in biosensor terminology. Additionally, the ERNN improves computational efficiency while maintaining high accuracy and precision. Further, the AMF-ERNN achieves a superior trade-off between accuracy and quality of translation, hence demonstrating its robustness in translating biosensor signals into text with minimal errors. This improvement by the AMF-ERNN model overcomes some limitations of the existing methods and hence provides a better answer for cross-cultural communication applications.

6. Conclusion

The transformational potential of a biosensor, especially a wearable type of sensor, in cross-cultural communication and more specifically in the translation of SL systems. The introduction sets the background of the AMF-ERNN model regarding how advanced AI algorithm applications can improve signal-to-text translations from wearables with a more accurate result in cultural sensitivity. To demonstrate the ability to capture subtle hand movements and gestures required for effective SL translation using techniques, such as sensors and motion detection. The results further highlight the importance of standardized English terminology in the accessibility and applicability of biosensor systems across a range of linguistic and cultural contexts. The proposed method outperformed the existing methods by achieving precision (98.2%), accuracy (98.5%), recall (98.3%), F1-score (98.4%), and WER (35.5%). With advancements in biosensor technologies, their integration into communication systems will bring forth the promise of breaking language barriers, accessibility for the hearing-impaired population, and increased global inclusivity. Maximum benefits would be achieved by doing more research in standardizing technical terms and developing culturally relevant translation strategies. This research provides the fundamental base for future innovations that support more efficient, globally relevant biosensor applications in communication technologies.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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