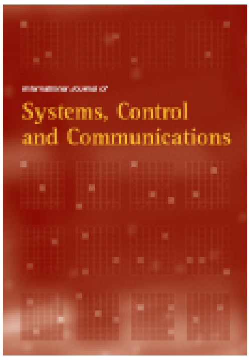

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Ponnusamy Lingeswari, Daniel Pavunraj, Mariappan Kanagavalli, Karuppasamy Manikandan

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Identification of Tamil Sign Language using Hamiltonian deep neural network

Ponnusamy Lingeswari*

Department of Electronics and Communication Engineering,
P.S.R. Engineering College,
Sivakasi, Tamil Nadu, India
Email: lingeswari@psr.edu.in
*Corresponding author

Daniel Pavunraj

Department of Artificial Intelligence and Data Science,
Vel Tech Multi Tech Dr. Rangarajan
Dr. Sakunthala Engineering College,
Chennai, Tamil Nadu, India
Email: pavunrajan27@gmail.com

Mariappan Kanagavalli

Department of Electronics and Communication Engineering,
P.S.R.R. College of Engineering,
Sivakasi, Tamil Nadu, India
Email: kanagavalli@psrr.edu.in

Karuppasamy Manikandan

Department of Computer Science and Engineering,
P.S.R. Engineering College,
Sivakasi, Tamil Nadu, India
Email: manikandan.k@psr.edu.in

Abstract: Sign language consisting of various hand patterns, serves as a vital communication medium for conveying messages, sharing knowledge, and expressing ideas among the deaf community. This research addresses the challenge of recognising Tamil Sign Language (TSL) by proposing a novel identification method using a Hamiltonian deep neural network (HDNN). The primary objective is to maximise the accuracy and reliability of TSL recognition, especially for real-time applications. The dataset comprises real-time images of 12 vowels, 1 Aayutha Ezhuthu, and 18 consonants, collected from 110 different signers. To address noise in the images, an iterative guided filtering (IGF) method is employed for preprocessing. Subsequently, feature extraction is performed using residual exemplars local binary pattern (RELBP). HDNN is then applied to classify the signs. The performance of the proposed approach achieves 23.32%, 25.07%, 21%, 27.53%, and 30% higher accuracy and 14.09%, 19.63%, 28%, 18.45%, and 10.54% lower error rates compared to existing methods.

Keywords: Tamil Sign Language recognition; Hamiltonian deep neural network; HDNN; iterative guided filtering; IGF; residual exemplars local binary pattern; RELBP.

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Biographical notes: Ponnusamy Lingeswari is currently working as an Assistant Professor at Department of Electronics and Communication Engineering, P.S.R Engineering College, Sivakasi, Tamilnadu, India. Her research interests include wireless communication, cognitive radio and machine learning applications in wireless communications.

Daniel Pavunraj is currently working as an Assistant Professor at Department of Computer Science and Engineering, P.S.R.R. College of Engineering, Sivakasi, Tamil Nadu, India. His research interests include image processing and cloud.

Mariappan Kanagavalli is currently working as an Assistant Professor at Department of Electronics and Communication Engineering, P.S.R.R. College of Engineering, Sivakasi, Tamil Nadu, India. Her research interests include soft computing application in power system engineering.

Karuppasamy Manikandan is currently working as an Assistant Professor at Department of Computer Science and Engineering, P.S.R. Engineering College, Sivakasi, Tamil Nadu, India. His research interests include image processing, and machine learning.

1 Introduction

Communication using sign language (SL) is considered a vital ability for those who are deaf or have hearing loss (Sharma and Singh, 2020). A limited count of well-organised sign codes make up SL, which is commonly employed in these kinds of groups to communicate information (Weerasooriya and Ambegoda, 2022). Some SL identification programs have been developed recently due to advancements in machine learning and technology (Mistry et al., 2021). SL is used in various ways to translate them as voice or text for the applications of learning (Aliyev et al., 2022). Tamil is the most common language in India, which is essential to study effectively to enhance the communication skill of TSL (Punsara et al., 2020). Some SLs are American Sign Language (ASL), British Sign Language (BSL), Chinese Sign Language (CSL), Japanese Sign Language (JSL) (Solak et al., 2024). The research field on Indian Sign Language (ISL) dependent recognition tools is wide as there are 22 official languages in India, including Tamil, Hindi, Bengali, Devnagiri, Telugu, Marathi, and others. Over the last 20 years, ISL-based research has undergone constant evolution (Fan et al., 2021; Galimberti et al., 2023). However, there have been very few contributions made in the field of TSL so far. Tamil is an ancient as well as regional language in the Indian state of Tamil Nadu.

Tamil Sign Language (TSL) recognition is crucial for effective communication within the deaf and hard-of-hearing community, yet existing systems often struggle with noise interference, inadequate feature extraction, and suboptimal classification accuracy. These challenges hinder the reliability of recognition systems. To address these issues, there is a pressing need for an advanced method that improves preprocessing, feature extraction, and classification. This research is motivated by the goal to enhance TSL recognition through innovative techniques such as iterative guided filtering (IGF) for noise reduction and Hamiltonian deep neural networks (HDNN) for precise classification, ultimately contributing to better communication accessibility and efficiency in various applications.

This paper proposes a new computational intelligence dependent Tamil Sign Language using Hamiltonian deep neural network (TSLI-HDNN) approach. Firstly, it employs an IGF method for preprocessing, which significantly improves noise reduction in digital images, enhancing overall image quality. Secondly, it utilises a unique area-based analysis approach for feature extraction, focusing on edge and interior pixels to capture critical SL features more effectively. Finally, the use of HDNN for classification is a novel application that ensures high accuracy and robust validation, setting it apart from existing methods. This combination of innovative preprocessing, feature extraction and classification techniques represents a significant advancement in the field of SL recognition. This computer-based assistive technology provides hearing-impaired people with the ability to adjust, operate, sustain and communicate with common people. It also increases the practical capacity of people with disabilities.

The major concepts of this research are summarised here,

- Introduced an IGF method that effectively reduces noise in TSL digital images, improving image quality and preprocessing accuracy.
- Developed an area-based analysis technique for feature extraction, focusing on edges and interior pixels of the images to capture critical features of Tamil signs more accurately.
- Applied HDNN for the precise classification of TSL images, ensuring robust validation and improved recognition performance.
- Demonstrated the capability of the HDNN to categorise identified patterns into distinct classes, enhancing the overall accuracy of TSL identification systems.

Remaining paper is arranged as: Section 2 analyses the literature survey, Section 3 elucidates the proposed approach, the results are shown in Section 4, and finally, conclusions is presented in Section 5.

2 Literature survey

Musthafa and Raji (2022) have suggested real-time ISL recognition system. The suggested method provides a system prototype that can automatically identify SL, thus deaf and dumb people transfer the message with normal people successfully. Image processing models were considered to determine the fingertip position of static pictures and converted them to text. The suggested method can realise the signer's pictures that were taken in real-time when the testing phase. System provides real-time recognition of Indian SL using CNNs for feature extraction and image processing techniques for fingertip detection, showing high precision in recognising static signs. However, its reliance on static images and a small dataset limits its ability to handle dynamic gestures and broader real-world variability.

Sharma and Singh (2022) have presented deep learning method dependent Recognition of ISL. It provides high accuracy with low working time. SLRS depending on computer-vision under deep learning approach was presented. In this manuscript, identification of TSLI-HDNN is proposed:

1 huge dataset of ISL was generated by 65 users in unrestrained context

2 intra-class variance in database to maximise the generalisation capacity.

This study offers a deep learning-based approach for ISL recognition that boasts high recall and a significant dataset generated from 65 users in varied contexts, enhancing the model's generalisation capacity. However, while the approach shows a lower error rate, the increased computation time may pose challenges for real-time applications, and the reliance on affine transformations might not capture all the complexities of natural gesture variations.

Petkar et al. (2022) have presented real-time SL recognition scheme for hearing and speech impaired people. A new method for SL identification with the help of OpenCV (a python library) for pre-processing imageries and extracting diverse skin toned hands from the background. The suggested system leverages OpenCV for efficient image pre-processing and YOLOv5 for fast and accurate gesture detection, while integrating CNNs for classification and a speech-to-sign translation module using the Web-Speech API and NLTK, offering a portable, cost-effective, and user-friendly solution for both deaf/mute communication. However, the system's reliance on video-based SL libraries may limit flexibility in recognising diverse gestures, and performance in real-world environments with varying conditions remains to be fully validated.

Soji and Kamalakannan, (2023) have presented Machine learning models to intelligent SL identification with classification. It analyses machine language techniques and employs ISL to recognise basic SL motions in pictures and videos. Preprocessing and feature extraction are applied to images to enhance the functionality of deployed models. It demonstrates effective machine learning approaches for ISL recognition, achieving 84% accuracy with the Random Forest model while focusing on pre-processing and feature extraction to enhance performance. However, the reliance on a specific dataset may limit the findings generalisability, and the relatively lower recall and F-score indicate that improvements were still needed for comprehensive gesture recognition.

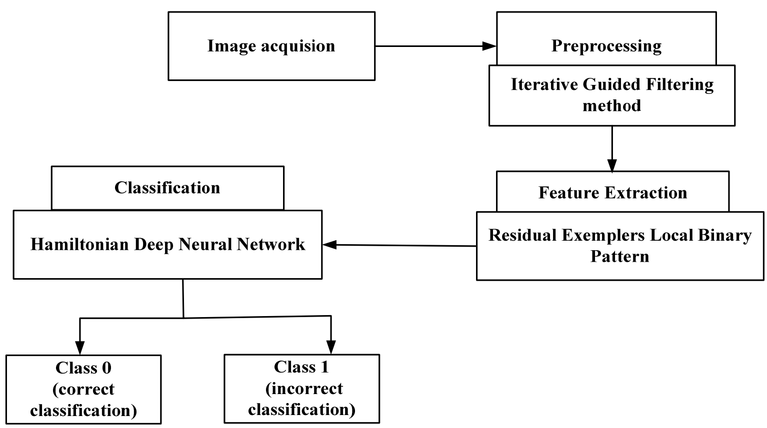
Katoch et al. (2022) have presented SURF with SVM and CNN basis ISL recognition system. To realise alphabets (A–Z) along digits (0–9) in a live video stream then output the expected labels in text along speech format, the bag of visual words (BOVW) model was introduced. The system integrates SURF features with SVM and CNN for ISL recognition, successfully identifying letters and digits in live video streams while offering an interactive GUI for user accessibility and higher AUC performance. However, the reliance on skin colour for segmentation may lead to challenges in varying lighting conditions, and the higher computation time could hinder real-time applications in fast-paced environments.

Raj et al. (2023) have presented Tamil handwritten character recognition scheme utilising statistical algorithmic modes. It provides a detailed analysis of locational and directional approaches along with various zone and quad method combinations for handwritten character recognition in Tamil. The character's image was first split into nine equal zones, and the directional algorithmic approach was used to extract the structural characteristics from each zone. Research presents a robust framework for recognising Tamil handwritten characters, utilising a two-stage feature extraction process that combines locational and directional approaches to effectively handle the complexities of a large character set. However, the reliance on specific zone and quad methodologies may not fully account for all variations in handwritten styles, and issues with unwanted loops and curves in the initial classification stage suggest there was still room for perfection in accuracy.

3 Proposed methodology

Identification of TSLI-HDNN is discussed in this section. It comprises four stages, like Data acquisition, pre-processing, feature extraction, TSL classification. Figure 1 represents the block diagram of TSLI-HDNN method. The explanation about each stage is specified below.

Figure 1 Proposed TSLI-HDNN methodology



3.1 Data acquisition

In this step, real-time TSL imageries were collected for experimentation, including representations of 12 vowels, 1 Aayutha Ezhuthu, 18 consonants through 110 signers. A total of 130 imageries were collected for vowels and 180 imageries for consonants, resulting in a comprehensive dataset for training and testing purposes.

For the proposed algorithms, the dataset was split into training and testing subsets to accurately evaluate performance. Specifically, 70% images are used for training the model, remaining 30% for testing. This results in 91 vowel images and 126 consonant images for training, and 39 vowel images and 54 consonant images for testing. This split ensures that the model is trained effectively while retaining a sufficient number of images for rigorous testing, allowing for a robust evaluation of the proposed method's accuracy and effectiveness.

Data augmentation

The data augmentation process is crucial for enhancing the robustness and generalisation ability of the TSL recognition model. A total of 310 hand shape images, including 130 for vowels and 180 for consonants, were collected from diverse signers. By introducing random changes to the original images, data augmentation significantly increases the training dataset.

Simple image rotations, flipping operations, and scaling strategies are some of the random transformation techniques used. Specifically, images are subjected to the following transformations: rotating right 90°, rotating left 90°, flipping vertically, flipping horizontally, and rotating 180°. Additionally, random scaling and translations are applied to simulate variations in hand positions and sizes. As a result, the image count is increased significantly through augmentation. Assuming three augmentations per original image, the total number of augmented images becomes 930. This increase in augmented images enhances the network's ability to learn suitable features, thereby improving the performance of the model. The augmented imageries are then used as input of the classification procedure. The Augmented Data Statistics are summarised in Table 1.

Table 1 Augmented data statistics

Category	*Original images*	*Augmentation factor*	*After augmentation*
Vowels	130	3	520
Consonants	180	3	720
Total	310	-	1,240

3.2 Pre-processing under IGF

In this section, preprocessing using IGF is discussed. IGF offers several advantages, particularly for TSL recognition. It effectively removes noise while preserving critical details like edges, ensuring that key features such as hand shapes and gestures remain intact. The filter adapts to the image content, providing improved clarity without distorting important structures, which enhances the input quality for subsequent feature extraction and classification stages. And to work with filtering images and various channels IGF method is applied. It includes input sign image *H* and preprocessed image *P* and is represented in equation (1),

$$P_j = b_l I_j + c_l \quad j \in \alpha_l \tag{1}$$

where α_l is square window, I_j represents input pixel intensity, the coefficients b_l and c_l are constants. Iterative guided filter has two stages, like removing and restoring. If the scale less than β_l filter size. Therefore, the filter is applied initially and is represented in equation (2),

$$F_i = \frac{1}{S} \sum_{i \in \delta} e^{\left(-\left(\frac{|i-j|}{2\beta_l}\right)\right)} \tag{2}$$

Let $K_j = \sum_{i \in \delta} e^{\left(-\left(\frac{|i-j|}{2\beta_l}\right)\right)}$ is used for normalisation, β_l denotes standard deviation, δ signifies filter sub-window. It shows scale sensing properties of iteration guided filter. Noise is slowly recollected and it is equal to the Tamil sign image and is represented in equation (3),

$$X_{i,j}(I^t) = \frac{1}{|\delta^2|} \sum_{j:(j,i) \in \delta j} \left[1 + \frac{(I_j - I_j)(\overline{I}_i - \overline{I}_l)}{\beta_l^2 + \in} \right] \tag{3}$$

where $X_{i,j}(I^t)$ is the filtered value. IGF can accurately remove noise. IGF removes noise from Tamil Sign Language digital (TSLD) images by applying a local linear model that preserves important structures, such as hand shapes and edges, while smoothing out noisy regions. The filter operates iteratively, refining the image with each pass to eliminate subtle noise without distorting critical details. By using the image itself as a guide, it maintains the clarity of edges and small-scale details, essential for accurate sign recognition. This method enhances image quality, reduces unwanted noise, and ensures that key features necessary for recognising Tamil sign gestures are preserved effectively. Thus the Tamil sign input image successfully fed into feature extraction phase.

3.3 Feature extraction utilising residual exemplars local binary pattern

In this section, Feature extraction using residual exemplars local binary pattern (RELBP) is discussed. The significant features from pre-processing are extracted using RELBP technique. Using RELBP for feature extraction, advantages including enhanced feature discrimination that effectively captures local texture and structural information, which is crucial for differentiating between similar signs in TSL. The extracting features using RELBP are explained as follows, initially separate the preprocessed image as 2 × 2 size overlapping block and get $(I - 2) \times (J - 2)$ blocks. By using signum function, extract binary features from every block. The signum function is represented in equation (4),

$$b(j) = sig(mt, bt) = \{0, mt \le bt, j = \{0, 1, 2, ..., 8\} \tag{4}$$

here mt implies neighbour pixel, bt implies centre pixel of 2 × 2 block, $b(j)$ represents binary feature. Change in bits to a decimal value and is represented in equation (5),

$$value(n, s) = \sum_{j=1}^{7} b(j) * 2^{7-j}, n = \{1, 2, ..., X - 2\}, s = \{1, 2, ..., U - 2\} \tag{5}$$

where n represents row index, s represents column index. Develop a RELBP executed image using values. Histogram of the RELBP executed image can be extracted. The extracted feature are explained as follows.

3.3.1 Bounding box

It is distinct in size with shape than the object's look and it denotes the physical appearance of the object.

3.3.2 Centroid

It is mean part of points in the associated directions.

3.3.3 Area

Area can be defined as the collection of pixels exactly identified in the region of the object.

3.3.4 Perimeter

Perimeter is said to be the total pixels across the boundary of each region at the sign image.

3.3.5 Equidistance

Equidistance can be defined as the length of minimum way between two points and also it denotes the length of an object.

3.3.6 Roundness

Roundness computes the connected appearance of an object grouped together in the edge area.

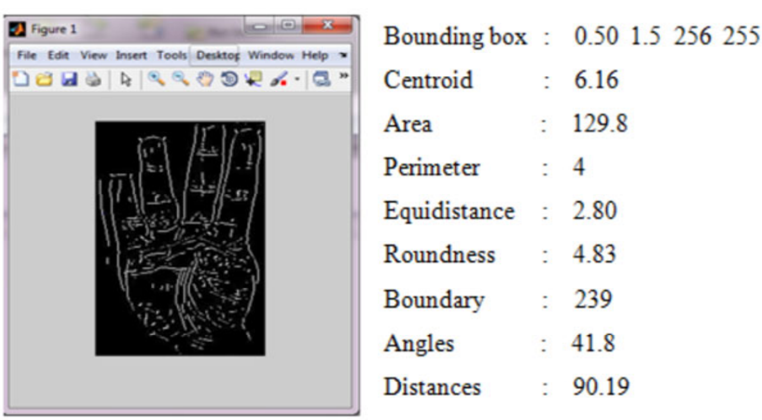
3.3.7 Number of edge

Number of edge tracks the required count of edge of space in image.

3.3.8 Angles

It forms through equal separation of two planes in an object.

Figure 2 Features extracted from TSL image (see online version for colours)



3.3.9 Distance

Distance among the actual pixel shows distinct value of an object. Therefore, RELBP technique extracts the above mentioned features, these extracted features are fed into TSL identification phase. Figure 2 shows the visual examples of extracted features.

3.4 TSL identification utilising HDNN

TSL identification utilising HDNN is discussed here. Utilising HDNN for TSL identification offers several advantages, including improved accuracy and robust feature extraction that enhances the recognition of subtle differences in signs, even in noisy environments. The HDNN effectively handles variability in sign execution, ensuring reliability in real-world applications, and demonstrates enhanced generalisation to unseen data. Its ability to process sequential images allows for the incorporation of context and movement, crucial for accurate interpretation. Furthermore, they can integrate multimodal inputs, such as audio or sensor data, providing a richer context for recognition. These advantages make HDNNs particularly suited for addressing the complexities of TSL identification, which results increasing accuracy and communication for deaf including hard-of-hearing community. The process of solving TSL classification problems can be rectified by the most prior option of selecting TSL identification technique. Extracted features are classified into two group class 1 and class 0. Consider the first-order TSL system and is represented in equation (6)

$$x(u) = e\left(x(u)\right), \alpha(u), \quad 0 \le u \le S \tag{6}$$

where $x(u)$, $x(0) = x_0$ and $\alpha(u) \in S$ is a vector of parameters. TSL digital images accuracy is computed using Hamiltonian neural networks in this classification phase. Therefore, time-varying Hamiltonian is represented in equation (7)

$$x(u) = K(u)\frac{\alpha J\left(\left(x(u)\right), u\right)}{\alpha x(u)}, x(0) = x_0 \tag{7}$$

where $K(u)$ time is varied Hamiltonian series. To recover the classified SL, consider the following Hamiltonian function and is represented in equation (8),

$$h\left(x(u), u\right) = \left[\alpha\left(J(u)x(u) + c(u)\right)\right]^t 1_m \tag{8}$$

where h is called Hamiltonian network and α is called activation function and $J(u)$ is the scalar unit. The activation functions and the logistic function for the language system are represented in equation (9),

$$\begin{aligned}\frac{\alpha J\left(x(u), u\right)}{\alpha x(u)} &= \frac{\alpha\left(S(u)x(u) + c(u)\right)}{\alpha x(u)} \frac{\alpha\left(H(u), u\right)}{\alpha\left(S(u)x(u)\right)c(u)} \\ &= S^t(u)\beta\left(S(u)x(u) + c(u)\right)\end{aligned} \tag{9}$$

where $\alpha x(u)$ is represented by HDNNs, $S^t(u)$ is the sub derivative function. β is the activation function. HDNNs are trained by solving the minimising the SLs by class 0 and is represented by equation (10)

$$\min \frac{1}{t}\sum_{k=1}^{t} K\left(e_M\left(y_M, \alpha_M\right)\right), b^l + T(\alpha) \tag{10}$$

where α denotes the trainable parameters, e_M represents error term, y_M represents target value. When considering gradient descent to lessen in every iteration and classify the vector α as class 1 and is represented in equation (11)

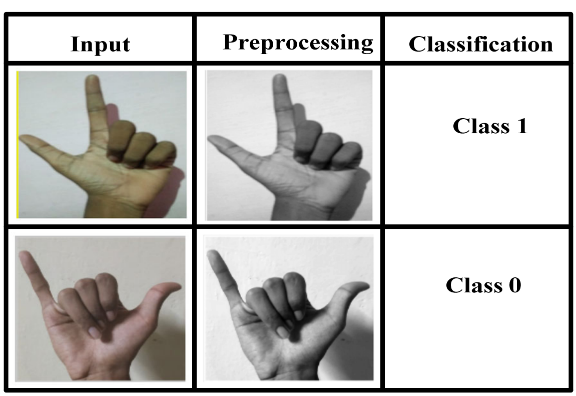
$$\alpha^{(K+1)} = \alpha^K - \delta.\eta_{\beta(K)} K \tag{11}$$

where K refers iteration number, δ refers learning rate, $\eta_{\beta(K)}$ refers loss function. TSL is successfully classified using HDNN with class 0 and class 1 accurately where class 1 represents correct pattern and class 0 represents wrong pattern respectively.

4 Result with discussion

The experimental results of the proposed identification of TSLI-HDNN are discussed in this section. Simulation is done in MATLAB. The suggested TSLI-HDNN method has achieved feasible outcomes under the mentioned metrics. the results of the TSLI-HDNN are analysed with existing methods: Real-time ISL recognition system (RTISL-RS), recognition of Indian Sign Language utilising deep learning method (RISL-CNN), real-time sign language recognition scheme for hearing and speech impaired people (RTSLR-HSIP), machine learning approaches to intelligent sign language recognition and classification (ML-ISLRC) and SURF with SVM and CNN basis Indian Sign Language recognition system (ISLRS-CNN) respectively. Figure 3 shows the output image for TSL identification.

Figure 3 Output image for TSL identification (see online version for colours)



4.1 Performance measure

To validate the robustness of the proposed technique, the following performance metrics are considered.

4.1.1 Accuracy

This is the capacity to calculate accurate value through equation (12).

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{12}$$

where *TP* depicts true positive, *TN* refers true negative, *FP* symbolises false positive, *FN* implies false negative.

4.1.2 Precision

It assess the accuracy of a classification method, specifically in binary or multi-class classification tasks. It determines the ratio of properly predicted positive instances out of all instances that projected as positive. It is expressed in equation (13)

$$Precision = \frac{TP}{(TP + FP)} \tag{13}$$

4.1.3 Recall

This is termed as sensitivity that measures a model's capacity to properly identify positive instances out of every real positive instances. It is computed by equation (14)

$$Recall = \frac{TP}{TP + FN} \tag{14}$$

4.1.4 F1-score

This is the harmonic mean of precision and recall, and is scaled by equation (15)

$$F1\text{-}score = 2 \times \frac{recall \times precision}{recall + precision} \tag{15}$$

4.1.5 Specificity

The rate of correctly identified negative instances out of all actual negative instances is determined using equation (16)

$$Specificity = \frac{TN}{TP + FP} \tag{16}$$

4.1.6 Error rate

The ratio of true positive to true negative cases is incorrectly predicted. This is computed by equation (17)

$$Error\ rate = (1 - Accuracy) \tag{17}$$

4.2 Performance analysis

Figures 4 to 7 and Tables 2 and 3 portray the performance analysis of proposed TSLI-HDNN method. Here, the performance metrics are scrutinised. The effectiveness of the TSLI-HDNN is compared with existing RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN models, respectively.

Figure 4 Accuracy analysis (see online version for colours)

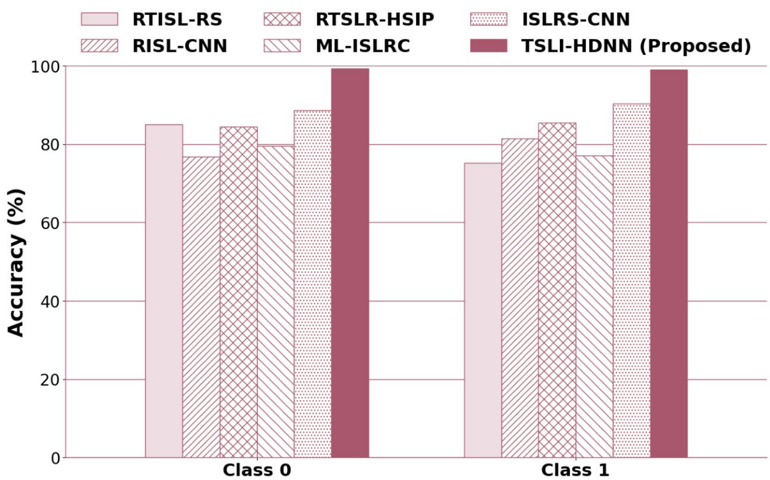


Figure 4 shows performance analysis of accuracy. A high accuracy specifies that the model effectively distinguishes between correct (class 1) and incorrect (class 0) signs, minimising both false positives and false negatives. Here, the TSLI-HDNN method provides 32.21%, 17.56%, 28%, 34.01%, 14.62% better accuracy for class 0; 25.45%, 15.89%, 25%, 30.45%, 29.54% better accuracy for class 1 compared with existing RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN, respectively.

Table 2 tabulates the performance analysis of precision, recall and F1-score. The precision analysis of the proposed method using HDNN shows significant improvements in accurately classifying correct signs. Precision, which computes the rate of true positives (correct signs) out of all predicted positives, is enhanced by the use of IGF for noise reduction and RELBP for effective feature extraction. Here, the proposed TSLI-HDNN method provides 22.21%, 27.56%, 24.7%, 14.01%, 24.62% better precision for class 0; 25.45%, 30.89%, 28.65%, 31.45%, 29.54% better precision for class 1 compared with existing methods like RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN, respectively.

In the context of the proposed approach for recognising TSL using HDNN, recall is essential because it reveals the model's proficiency in identifying all valid signs from the diverse dataset of real-time images. High recall ensures that most of the TSL signs are recognised accurately, which is essential for effective communication within the deaf community. The proposed TSLI-HDNN method provides 20.21%, 23.01%, 24.7%, 4.01%, 9.62% better recall for class 0; 25.45%, 10.89%, 28.65%, 30.45%, 29.54% better recall for class 1 compared with existing RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN, respectively.

In the context of the proposed approach for recognising TSL using HDNN, the F1-score is crucial for evaluating the model's performance, as it balances the trade-off amid correctly identifying signs (recall) and ensuring that those identified as correct are indeed accurate (precision). The proposed TSLI-HDNN method provides 25.21%, 29.01%, 24.7%, 4.01%, 19.62% better F1-score for class 0; 25.45%, 30.89%, 28.65%, 20.45%, 29.09% better F1-score for class 1 compared with existing RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN, respectively.

Table 2 Precision, Recall and F1-Score analysis

Methods	*Precision (%)*		*Recall (%)*		*F1-score (%)*	
	Class 0	*Class 1*	*Class 0*	*Class 1*	*Class 0*	*Class 1*
RTISL-RS	77.9	79.5	83.28	72.25	76.1	81.2
RISL-CNN	85.9	87.6	78.8	81.4	85.8	75.4
RTSLR-HSIP	80.35	83.65	70.3	88.2	84.5	85.5
ML-ISLRC	79.9	78.6	66.8	77.4	71.8	80.4
ISLRS-CNN	67.35	77.65	73.3	81.2	65.5	75.5
ISLRS-CNN (proposed)	97.65	97.85	97.2	97.4	97.5	98.1

Figure 5 Performance analysis of computation time (see online version for colours)

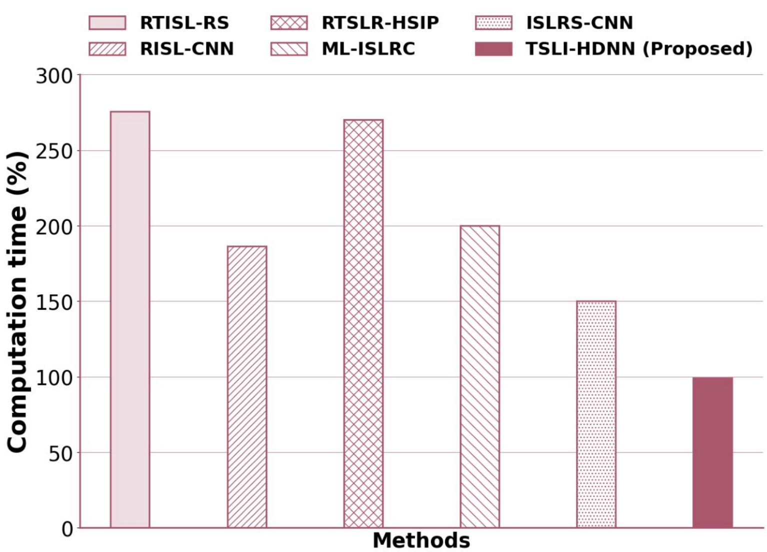


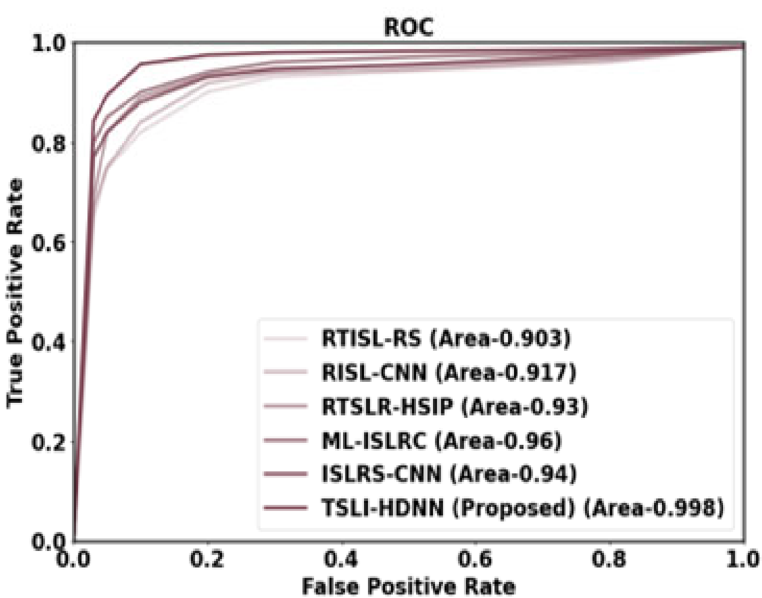
Figure 5 depicts computation time analysis. Here, the proposed approach for TSL using HDNN reveals a structured breakdown of processing stages. The most time-consuming aspect is model training, which can range from minutes to hours based on the network's complexity and dataset size. Overall, while the training phase demands considerable computation time, the proposed approach ultimately delivers quick classification speeds, making it effective for real-time TSL recognition. The proposed TSLI-HDNN method attains 20.76%, 14.98%, 25.05%, 18.98% and 30% lower computation time compared with existing methods like RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN, respectively.

Table 3 Performance analysis of Error rate and Specificity

Methods	*Error rate (%)*		*Specificity (%)*	
	Class 0	*Class 1*	*Class 0*	*Class 1*
RTISL-RS	14.9	24.8	85.1	89.2
RISL-CNN	23.2	18.6	88.1	79.2
RTSLR-HSIP	15.5	14.5	77.1	87.2
ML-ISLRC	20.5	22.9	81.1	71.2
ISLRS-CNN	11.4	9.6	72.1	85.1
ISLRS-CNN (proposed)	0.7	0.9	99.45	98.7

Table 3 depicts error rate and specificity analysis. In the context of the proposed HDNN approach, the error rate analysis involves evaluating how often the model misclassifies signs, including both instances where incorrect signs are identified as correct and where correct signs are missed. A comprehensive error rate analysis aids recognise specific areas where the method may struggle, such as distinguishing similar signs or recognising signs from different signers. Here, the proposed TSLI-HDNN method provides 21.21%, 19.01%, 20.7%, 14.01%, 19.62% lower error rate for Class 0; 25.45%, 29.89%, 8.65%, 20.45%, 9.09% lower error rate for Class 1 compared with existing methods like RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN, respectively.

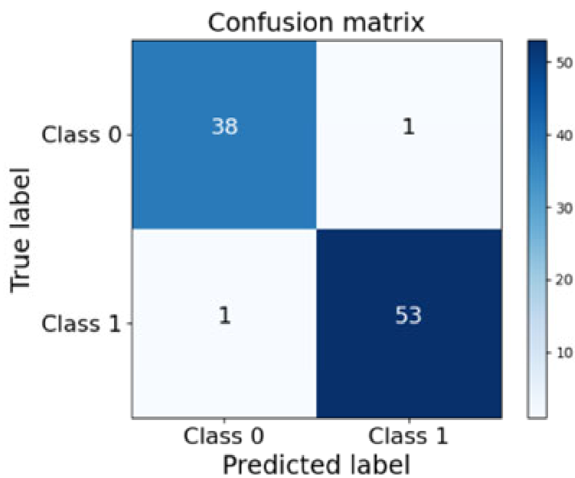
Figure 6 ROC analysis (see online version for colours)



In evaluating the HDNN's performance, a high specificity indicates that the model reliably identifies incorrect signs, thereby reducing the likelihood of misinterpretation in real-time applications. This is essential for maintaining communication accuracy within the deaf community. The proposed TSLI-HDNN method provides 30.21%, 27.56%, 28%, 14.01%, 28.62% better specificity for class 0; 24.45%, 10.89%, 25%, 20.45%, 29.54% better specificity for class 1 compared with existing methods like RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN, respectively.

Figure 6 shows ROC analysis. This is defined as a graphical representation to evaluate the classification performance at various threshold values. It exemplifies the trade-off among sensitivity (TPR) and specificity (FPR) on some threshold values, offering insight into the method's capacity to separate among positive and negative classes. The proposed TSLI-HDNN method attains 10.76%, 16.98%, 25.05%, 8.98% and 26.44% higher ROC compared with existing methods like RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, ISLRS-CNN, respectively.

Figure 7 The performance of the TSLI-HDNN utilising confusion matrix (see online version for colours)



4.3 Discussion

The proposed approach for TSL identification using HDNN, combined with pre-processing via iterated guided filtering and feature extraction under RELBP, offers a highly effective solution for recognising hand gestures with improved accuracy. Iterated guided filtering enhances input image quality by removing noise while preserving essential edges and features. RELBP focuses on extracting key geometric attributes, enabling precise differentiation between signs. HDNN then classifies these features into distinct categories with superior accuracy compared to traditional methods like RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, and ISLRS-CNN. The approach delivers higher accuracy and lower error rates, demonstrating significant advancements in TSL recognition, though further enhancement could be achieved by incorporating additional data augmentation techniques and exploring other neural network architectures.

5 Conclusions

This manuscript proposes an automatic TSL Identification scheme for knowledge acquisition and dissemination that was valuable for those with hearing impairments using machine vision applications. Initially, the digital imageries were preprocessing with IGF. Finding the structural features in the hand image during the feature extraction step was the primary goal. The effectiveness of image recognition systems is impacted by these qualities in different ways. HDNN identifies the images. The proposed TSLI-HDNN approach is executed in MATLAB. The efficacy of the TSLI-HDNN attains lesser computation time, higher recall, higher precision, compared with existing RTISL-RS, RISL-CNN, RTSLR-HSIP, ML-ISLRC, and ISLRS-CNN models respectively.

The proposed method for TSL recognition, while effective, has several limitations that warrant attention. It is specifically designed for TSL, limiting its applicability to other SLs, and the computational complexity of the HDNN may hinder real-time processing. Additionally, the system performance can be affected by variations in lighting, background, and sign execution speed, and the dataset may not capture the full diversity of TSL. Future work will focus on expanding the system to support multiple SLs, optimising the HDNN for faster processing, enhancing the dataset with more varied samples, and exploring advanced techniques like transfer learning to improve performance with limited data. Ultimately, deploying the system in practical settings will enhance accessibility and usability for everyday communication.

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