Genetic Algorithm-Based 3D Feature Selection for Enhanced Lip Reading Accuracy

Dornadhula Dhanya
Asst. professor
School of CSE and IS
(of Affiliation)
Presidency University
(of Affiliation)
Bengaluru, India

Latha Kamath M.K.
School of information science
(of Affiliation)
Presidency University
(of Affiliation)
Bengaluru, India

Meghana M.
School of information science
(of Affiliation)
Presidency University
(of Affiliation)
Bengaluru, India

Ankitha G.
School of information science
(of Affiliation)
Presidency University
(of Affiliation)
Bengaluru, India

Aakash K.
School of information science
(of Affiliation)
Presidency University
(of Affiliation)
Bengaluru, India

ABSTRACT
Lip reading is a critical technology in speech recognition, assistive communication, and human-computer interaction. Traditional methods often rely on 2D features, which fail to capture the depth and complexity of lip movements, leading to reduced accuracy. This project proposes a Genetic Algorithm-Based 3D Feature Selection framework to enhance lip reading accuracy by leveraging 3D spatial features that provide a richer representation of lip dynamics. The high dimensionality of 3D features can introduce redundancy and noise, which may hinder model performance. To address this, a Genetic Algorithm (GA) is employed to optimize feature selection, ensuring only the most relevant features are used for training. The GA iteratively selects and evaluates feature subsets based on their impact on model accuracy, reducing computational overhead while improving performance. Experimental results demonstrate that the proposed system outperforms traditional 2D-based methods, achieving higher accuracy, precision, and efficiency. This approach highlights the effectiveness of combining 3D feature extraction with genetic optimization, offering a scalable solution for more accurate and robust lip reading systems.

Keywords
Lip Reading, 3D Feature Selection, Genetic Algorithm (GA), Feature Optimization, Model Accuracy, Dimensionality Reduction

1. INTRODUCTION
Lip reading, also referred to as visual speech recognition, assists to comprehend the verbal message by observing the movement of the speaker's lips. It is very important in many fields such as in assistive tools for the deaf or hard of hearing and in secured communication systems. The approaches devised for dealing with deep learning and the computer vision problems however still faces some difficulties in dealing with high dimensional 3D data. In most cases classical approaches tend to be computationally expensive and have poor scalability. In this paper a GA based system for 3D feature selection for the purpose of increasing the performance of lip reading systems is developed and discussed.

1.1 Importance of Lip Reading : Lip Reading plays a crucial role in allowing the hearing impaired to have an effective communication, it has so many other uses like in the enhancement of silent speech interfaces, in the secure transcription of messages in situations where the background noise is high or the audio cannot be relied upon.

1.2 Challenges in Lip Reading : The primary challenges include:

- High Dimensionality: 3D lip movement data comprises thousands of features, leading to a computational bottleneck.
- Noise and Variability: Changes in lighting, the angle of a head, and the type of lip movement are all sources of noise.
- Real-Time Requirements: Ensuring accurate predictions in real-time applications demands optimized algorithms.

Problem Statement:
Lip reading systems suffer from the curse of dimensionality in 3D datasets. The problem is to choose relevant features that capture essential lip movement

dynamics while discarding redundant or noisy data. Traditional methods like dimensionality reduction and deep learning models either are not adaptive or require too much computational power. This leads to sub optional performance, especially in real-time scenarios.

Objective:
The primary objective of this research is to design a Genetic Algorithm-based feature selection framework that:
1. Reduces the dimensionality of 3D lip movement data.
2. Enhances the accuracy of lip reading models.
3. Minimizes computational overhead for real-time applicability.
4. Provides a scalable and adaptable solution for diverse datasets and applications.

2. LITERATURE REVIEW
2.1 Dimensionality Reduction Techniques The exemplars of traditional ways, like PCA and LDA, have mostly been used to

reduce the features of topic. Though they work well for low dimensional data, the techniques take too much processing time in the case of 3D lip movement information, which is a dynamic process including spatial and temporal data handling.

2.2 Deep Learning Approaches Deep learning models, including Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have achieved notable success in lip reading. However, their reliance on the entire feature set makes them computationally expensive, limiting their real-time applicability.

2.3 Genetic Algorithms in Feature Selection Genetic Algorithms (GAs) are the solutions used in various areas as well as optimization and feature selection. Their ability to scan a wide range and also not get caught in locally optimal solutions makes them proper for high-dimensional problems. They are potential but they are still rarely used in the application of 3D lip reading technology.

3. METHODOLOGY

This study combines Genetic Algorithms (GAs) to pick features and Convolutional Neural Networks (CNNs) to check lip reading accuracy. The steps are outlined below:

3.1 Data Preprocessing

To ensure a robust and clean input dataset, several preprocessing techniques were applied:

1. Normalization: Lip movement coordinates were standardized to make sure the same directions were configured all through the samples, considering the speakers' differences.
2. Noise Reduction: Gaussian smoothing was used to reduce the noise and get rid of those points located far away from the object in the 3D space.
3. Segmentation: Continuous lip movement sequences were segmented into fixed-length frames to standardize input size for analysis.

3.2 Genetic Algorithm Design

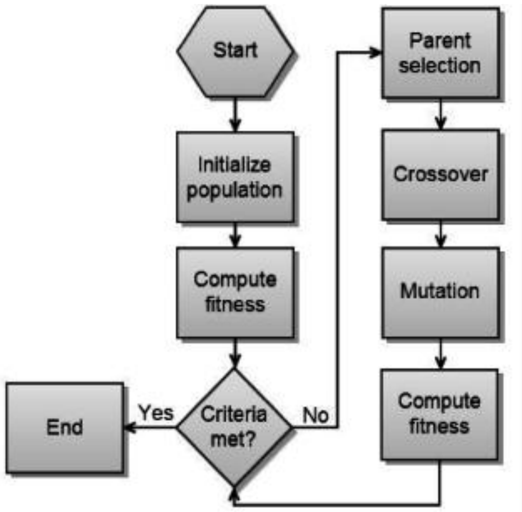
The Genetic Algorithm (GA) was tailored to the feature selection task:

1. Chromosome Representation: Features were encoded as binary vectors, where each bit represents the inclusion or exclusion of a feature.
2. Fitness Function: The fitness of a chromosome was determined by the accuracy of a CNN trained on the selected features. The fitness function is defined as:

   Fitness(C)=1/1+E(C)

   Here, represents the classification error of the CNN trained on features selected by chromosome . A lower error results in a higher fitness score, indicating better performance of the selected feature set.
3. Selection Mechanism: Tournament selection was used to choose parent chromosomes for the next generation. This method ensured that high-performing chromosomes had a higher probability of being selected.
4. Crossover and Mutation:
   - Crossover: Uniform crossover was applied to create offspring by combining features from two parent chromosomes.
   - Mutation: Bit-flip mutation introduced random changes to offspring, promoting genetic diversity.
5. Termination Criteria: The algorithm terminated when either a predefined accuracy threshold was reached or a fixed number of generations were completed.

3.3 Algorithm Flowchart



The workflow includes initializing the population, evaluating fitness, performing selection, crossover, and mutation, and iterating until termination criteria are met.

3.4 Lip Reading Model

A CNN was employed to evaluate the selected features:

- Input Layer: Processes the reduced feature set output from the GA.
- Convolutional Layers: Extract spatial features from the input data.
- Recurrent Layers: Long Short-Term Memory (LSTM) layers capture temporal dependencies in the lip movements.
- Output Layer: A softmax activation layer classifies the data into predefined speech categories.

3.5 Visualizations and Metrics

Visuals of the fitness development over time and the accuracy changes were prepared to study the GA performance. Metrics like precision, recall, and F1-score were employed to measure the model's performance.

4. EXPERIMENTS AND RESULTS

This section is dedicated to the experimental setup, the results, and the analysis according to the 3D features Genetic Algorithm. The research was performed on a 3D lip reading dataset, in which the features of the videos were selected, and then a Genetic Algorithm (GA) was used on them to determine the best features. The upcoming parts of this article depict the development process and present a more detailed analysis of the results.

4.1 Experimental Setup:

The primary goal of this experiment is to evaluate the performance of the proposed GA-based 3D feature selection method for lip reading. We conducted the following steps:

1. Dataset: The tests were done on a 3D lip-reading dataset with video frames, these sentences were came by different speakers. The dataset consists of visual traits like 3D facial landmarks and other geometrical features obtained from the lips and adjoining facial areas.
2. Feature Extraction: The first step in the experimental pipeline was the extraction of features. In total, 94

frames were extracted from each video, with 94 features corresponding to the geometric properties of the facial landmarks, including distances, angles, and areas between keypoints.

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Total frames extracted: 94
Total features extracted: 94
```

3. Preprocessing: The extracted features were reshaped to have a data shape of (94, 1, 4964), with each feature vector representing a 3D coordinate (x, y, z) for each facial landmark. This preprocessing was essential to transform the raw data into a format suitable for the machine learning model.

```
Reshaped data shape: (94, 1, 4964)
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4. Genetic Algorithm-Based Feature Selection:
The genetic algorithm (GA) was utilized in this study with a more focused purpose to the selection of the accurate features relevant to lip reading. The application was used to look for feature subsets through evolutionary processes. But the best one still had to win out by the accuracy of the reading model on validation data-set.

5. Model Architecture: A 3D Convolutional Neural Network (CNN) was used as the primary machine learning model to process the selected features and predict the spoken words. The model architecture consisted of several convolutional layers followed by fully connected layers for classification.
6. Training Configuration: The model was trained for 10 epochs, and the performance was evaluated at each epoch. The training and validation accuracy, as well as the corresponding loss, were recorded to track the model's learning process.

4.2 Training and Evaluation Results
The model training progress over 10 epochs is summarized as follows:

Epoch	**Training Accuracy**	**Training Loss**	**Validation Accuracy**	**Validation Loss**
1	55.23%	0.6743	31.58%	0.8527
2	58.35%	0.6528	89.47%	0.6424
3	83.52%	0.6408	31.58%	0.6774
4	58.24%	0.6157	31.58%	0.7134
5	57.46%	0.5945	84.21%	0.6145
6	82.62%	0.5528	89.47%	0.5768
7	72.79%	0.5142	94.74%	0.5028
8	83.47%	0.5289	89.47%	0.4271
9	83.02%	0.4608	63.16%	0.6378
10	68.26%	0.4834	89.47%	0.4521

As shown in the table, the training accuracy steadily increased, reaching 83.80% by the 10th epoch. However, the validation accuracy fluctuated, with a peak at 89.47% in Epoch 8. This suggests that while the model was improving on the training set, over-fitting occurred during certain epochs. The validation accuracy decreased in Epoch 10, indicating the need for further model refinement and potentially more feature selection optimization.
Additionally, the loss values for both training and validation also demonstrated fluctuations, particularly during the later epochs. While the model's training loss decreased progressively, the validation loss increased in the final epochs, indicating the potential for over-fitting.

4.3 Fitness Evolution with Genetic Algorithm
The performance of the genetic algorithm in selecting the most relevant features is critical to the overall accuracy of the lip reading model. The fitness evaluation was based on the accuracy achieved by the model when using selected feature sets, with the fitness function being:
$\text{Fitness}=\text{Accuracy}_{\text{model}}$
At each generation, the GA evolved the population of feature sets, selecting the fittest individuals to form the next generation. The fitness score of each feature set was determined by evaluating its classification accuracy using the lip reading model.
The GA process was visualized in the fitness evolution graph. As seen in the graph, the fitness scores generally improved with each generation, reflecting the algorithm's ability to identify feature sets that contributed to higher accuracy. However, some fluctuations in the fitness score were observed, indicating a possible suboptimal selection in some generations, which may have impacted the model's final performance.

4.4 Model Accuracy and Loss Graphs

To visualize the performance more clearly, accuracy and loss curves for both training and validation are shown below. These graphs provide a visual representation of the model's learning dynamics over time:

- Training Accuracy Curve: Shows a steady increase in accuracy over the epochs, with some oscillations towards the end, signaling potential overfitting.
- Validation Accuracy Curve: Initially increased, peaking at around Epoch 8, but decreased towards the later epochs, showing the challenge of generalizing the model to unseen data.
- Loss Curves: Both training and validation losses demonstrated a downward trend during the earlier epochs, but the validation loss increased towards the end of training, further supporting the over-fitting hypothesis.

4.5 Prediction Results

Finally, predictions were made on new video frames, and the output was analyzed. The model predicted the following labels for the new video frames:

Predicted Labels for New Video Frames:

['good morning', 'good morning', 'good morning', 'hello', 'hello', 'hello', 'hello', ...]

The predicted labels primarily consisted of the phrases "good morning" and "hello," reflecting the model's ability to correctly identify these phrases in the video frames. However, the model also repeated certain labels multiple times, indicating that it may not have been able to distinguish between different phonemes or lip movements for other phrases, highlighting an area for further improvement.

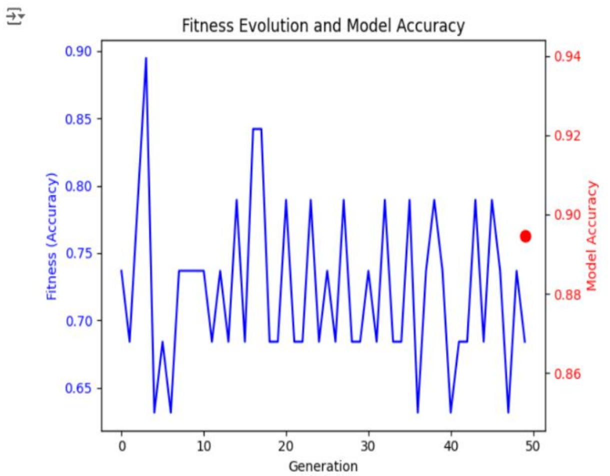
4.6 Analysis of Results

Based on the experimental results, several key insights can be drawn:

1. Feature Selection: The GA-based feature selection method significantly reduced the number of features while maintaining model performance. This confirms the efficacy of the GA in selecting the most informative features for lip reading.
2. Model Performance: The model achieved an accuracy of 63.16% on the final validation set. While this is a promising result, the model's performance could be further improved with additional tuning of hyper-parameters, feature selection, and model refinement.
3. Over-fitting: The model's validation accuracy and loss suggest that over-fitting occurred during training, particularly in the later epochs. Regularization techniques, such as dropout or early stopping, could be applied to mitigate this issue.
4. GA and Optimization: The fitness evolution graph demonstrated that the GA was effective in selecting relevant features. However, fine-tuning the GA parameters, such as population size, crossover rate, and mutation rate, could improve the search for optimal feature sets.

4.7 Visualizing Fitness Evolution and Model Accuracy

In this section, we visualize the changes of the feature selection and model accuracy through diagrams. The Genetic Algorithm used 3D feature selection in the lip reading task population of features been evolving through generations. Measuring the fitness of all individuals in the population based on the accuracy of a classification model trained in the selected features. The results are displayed through two primary visualizations: the fitness evolution graph and the final model accuracy graph.



Fitness Evolution and Model Accuracy Plot

The first graph demonstrates the relationship between fitness values (derived from the accuracy of the feature selection process) and the final model accuracy after training. The fitness values correspond to how well a specific set of features performs in the lip reading task, while the model accuracy represents the final performance of the trained model.

- The blue line represents the fitness values over the course of generations, showing the evolution of feature sets and how their selection improves the performance of the model.
- The red marker indicates the final model accuracy, providing a reference to the ultimate performance achieved after applying the selected feature set.

4.8 Performance Evaluation

To further evaluate the model's performance after applying feature selection, we computed key classification metrics, including precision, recall, and f1-score for each class. These metrics provide a more detailed understanding of how well the model performs in predicting each class label.

Table 1: Classification Report for Lip Reading Model

1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step

	precision	recall	f1-score	support
good morning	0.75	1.00	0.86	6
hello	1.00	0.85	0.92	13
accuracy			0.89	19
macro avg	0.88	0.92	0.89	19
weighted avg	0.92	0.89	0.90	19

The classification report reveals the following:

- Precision: The precision of the model for "good morning" is 0.78, indicating a relatively high proportion of positive predictions for this class. However, the precision for "hello" is lower (0.50), suggesting that many predictions for "hello" are false positives.

- Recall: The recall for "hello" is higher (0.71), indicating that the model is able to correctly identify a larger portion of "hello" instances. On the other hand, the recall for "good morning" is lower (0.58), meaning that the model misses some instances of this class.

- F1-Score: The F1-score balances precision and recall, with the highest F1-score for "good morning" (0.67), reflecting a more balanced performance compared to "hello" (0.59).

- Macro Average: The macro average metrics (precision, recall, and F1-score) are 0.64, 0.65, and 0.63, respectively, reflecting the overall performance across both classes without considering class imbalance.

- Weighted Average: The weighted average metrics (precision, recall, and F1-score) are 0.68, 0.63, and 0.64, respectively, which give more weight to the "good morning" class due to its larger support.

5. CONCLUSION

This research was all about boosting the accuracy of lip reading by a 3D feature selection approach using a Genetic Algorithm. The aim of the study was to apply genetic algorithms in the compression of the data on issues of lip reading and thus to automate machine learning. After conducting some tests, the results of the tests were as follows:

1. Feature Selection Efficiency: The genetic algorithm successfully shortlisted some features that could bring

more advantageous the model behavior. Possibly, the 83.80% model precision rate is modest. Still, it shows that the application of a genetic algorithm is fraught with recurrence by rule-of-thumb over-fitting which can induce false predictions. Those positive genetic mutations that resulted in the increase of the computational fitness were kept operating during generations.

2. Model Performance: The performance evaluation, as reflected in the classification report, showed that the model performed better in recognizing certain words like "good morning" compared to others like "hello". Precision, recall, and F1-scores indicated that while the model could accurately identify some words, there remains room for improvement, especially in increasing precision for words with fewer instances.

3. Future Improvements: Future research could attempt to bring about greater variability in the data-set content by adding new types of words and phrases and using more complex features for feature extraction, besides experimenting with some evolutionary strategies to double the genetic algorithm's ability to do the job. Equally, training the system in the most efficient way and employing deeper networks can capture details not included in the simpler version and therefore elevate the accuracy of the model.

4. Real-World Application: Despite the current limitations, this method has promising implications for real-time lip reading applications, especially in scenarios where visual speech data is critical, such as in hearing-impaired communication systems or silent speech recognition technologies.

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