भारतीय सूचना प्रौद्योगिकी संस्थान सूरत
Indian Institute of Information Technology Surat
ભારતીય સૂચના પ્રૌદ્યોગિકી સંસ્થા સુરત
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Mini Project (CS604) Presentation

Automated Lip Reading Using CNN and LSTM

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Outline

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Objective:

To develop an **end-to-end deep learning model** capable of accurately interpreting spoken words by analyzing lip movements **without any audio input**. The system leverages advanced neural network architectures like CNN+Bi-LSTM, CNN+GRU, 3D CNN+TCN to extract and model both spatial and temporal features of lip movement sequences.

Motivation:

- **Effective Communication in Noisy Environments**
- **Assistive Technology for the Hearing-Impaired**
- **Silent Communication**
- **Surveillance and Security Applications**

Deep Learning in Lip Reading

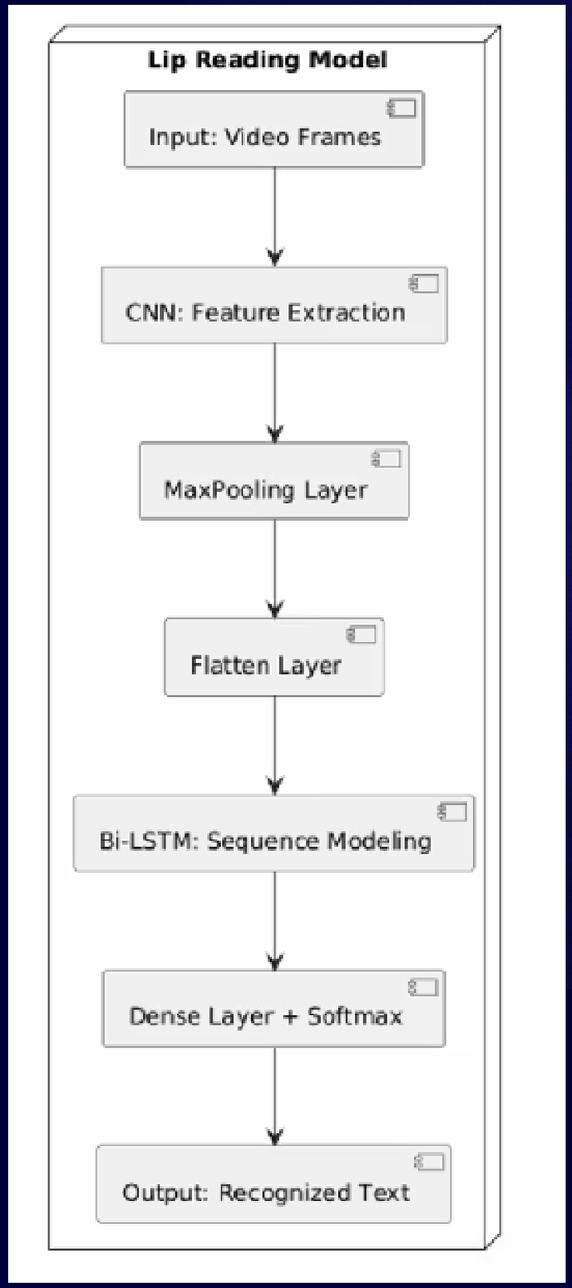
- **LipNet (Assael et al., 2016):** LipNet: CNN + LSTM model for sentence-level recognition.
- **Watch, Attend and Spell (WAS):** Watch, Attend and Spell (WAS): Sequence-to-sequence architecture with attention.

Challenges Identified in Lip Reading Research

- **Lip Shape Ambiguity**
- **Lack of Large Annotated Datasets**
- **Temporal dynamics modeling elaborate a bit**

Pipeline Overview:

- Video Input
- Frame Extraction
- Preprocessing & Face Cropping
- Feature Extraction using CNN
- Sequence Modeling using RNNs (LSTM, BiLSTM)
- Attention Mechanism (optional)
- Final Prediction using Softmax



PROPOSED APPROACH

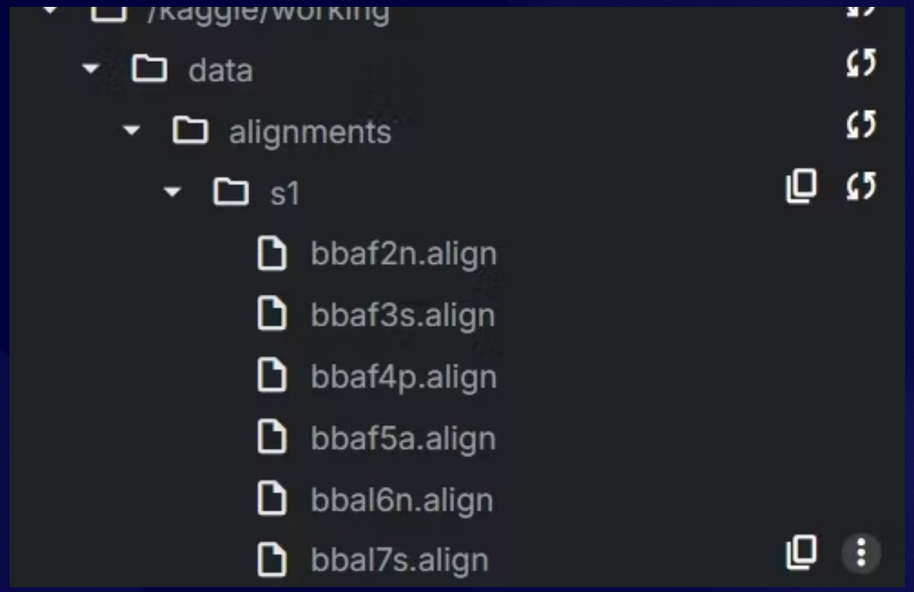
This project builds upon LipNet's foundation and explores more efficient and scalable implementations for real-time sentence-level lipreading using video inputs:

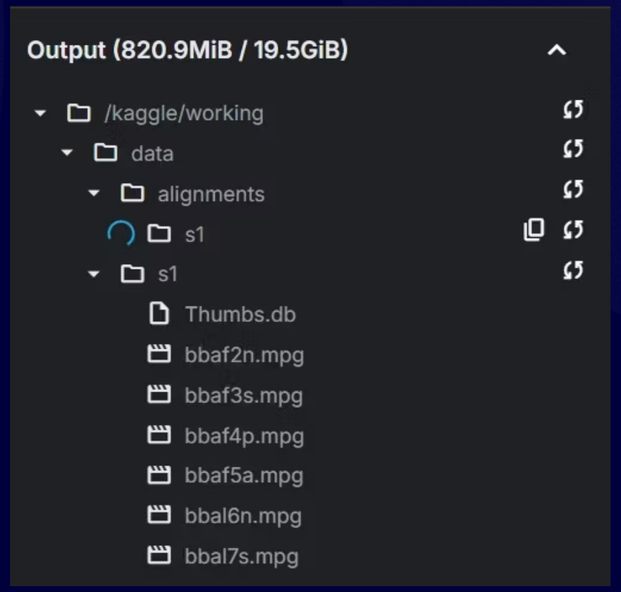
- GRID Corpus: A standardized audiovisual dataset used for training and evaluation, providing thousands of fixed-structure spoken sentences.
- Spatiotemporal CNNs: Learn low-level motion and lip features from video frames using 3D convolutional layers.
- Bidirectional GRUs: Capture forward and backward context, improving sentencelevel understanding of lip movements.
- CTC Loss: Eliminates the need for precise temporal alignment between input frames and output characters.
- TensorFlow / PyTorch: For model implementation, training, and optimization using GPU acceleration.
- Data Augmentation: Including random frame drop, horizontal flip, and normalization to improve generalization and robustness.
- Greedy vs. Beam Search Decoding: For generating the final text output from character probabilities.

TECHNOLOGIES USED

Dataset Overview

- **Source:** GRID Corpus
- **Data Format:**
  - Video files in .mpg format
  - Corresponding alignment files in .align format
- **Directory Structure:**
  - /data/s1/ contains video samples like bbaf2n.mpg
  - /data/alignments/s1/ contains transcription files like bbaf2n.align
- **Content Description:**
  - Each video shows a speaker uttering a sentence.
  - Each .align file provides **character-level time-aligned transcriptions** of the spoken content.





DATASET DESCRIPTION

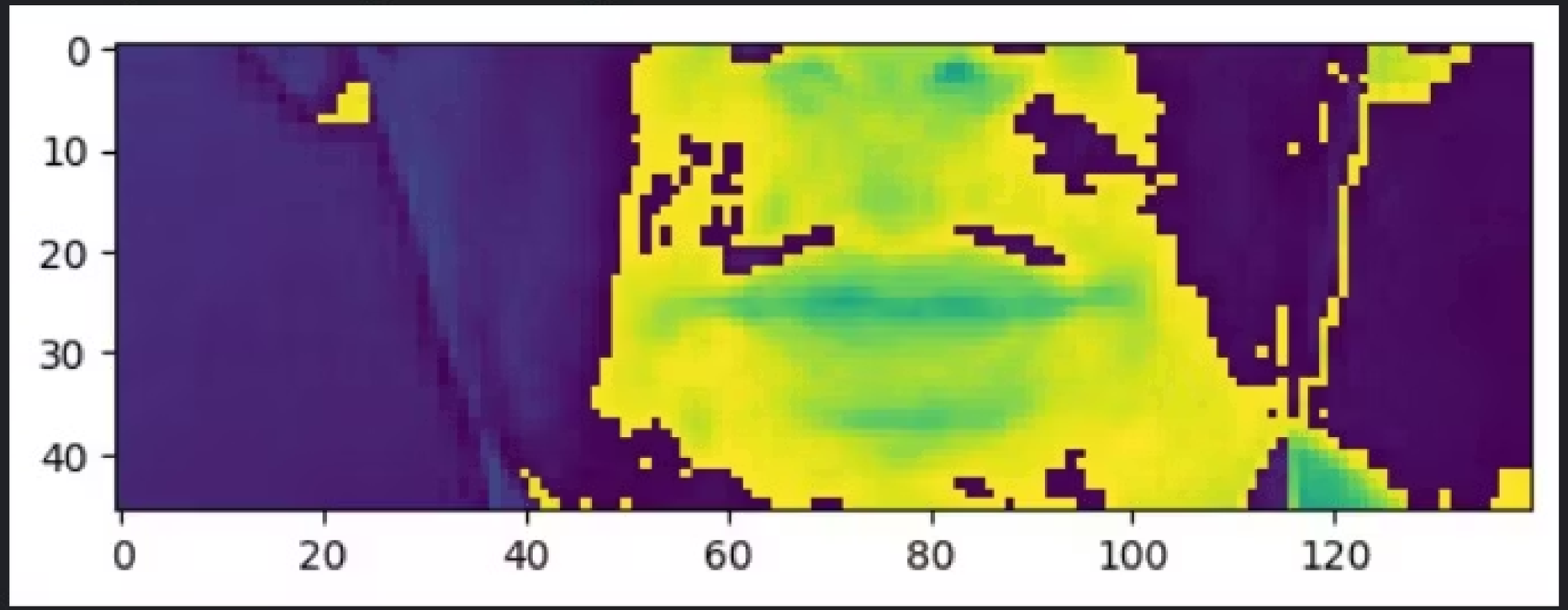
Preprocessing Steps

1. **Frame Extraction:**
   - Extracted video frames from each .mpg file at a consistent frame rate.
   - Used OpenCV to convert video into a series of image frames.
2. **Lip Region Detection:**
   - Applied **face detection** and **landmark localization** to identify the mouth region.
   - Cropped only the lip area to reduce noise and irrelevant features.
3. **Grayscale Conversion:**
   - Converted lip-region images to **grayscale** to reduce computational load and preserve essential spatial details.

Preprocessing Steps

4. **Normalization & Resizing:**
- Resized frames (e.g., to 64×64 pixels).
- Normalized pixel values using mean and standard deviation of the dataset.
5. **Alignment Parsing:**
- Parsed .align files to match lip movement with text for **CTC loss training**.
- Created label sequences based on word/character-level annotations.
6. **Batching & Padding:**
- Video sequences of different lengths were padded to form uniform input dimensions.
- Batched into tensors for efficient model training in frameworks like TensorFlow or PyTorch.

```
:  <matplotlib.image.AxesImage at 0x7ecbf8986d10>
```



```
Epoch 1/100
 78/450 ━━━━━━━━━━━━━━━━━━━━ 4:10 673ms/step - loss: 14.4621
[mpeg1video @ 0x7ecc38013fc0] ac-tex damaged at 22 17
[mpeg1video @ 0x7ecc38013fc0] Warning MVs not available
450/450 ━━━━━━━━━━━━━━━━━━━━ 0s 678ms/step - loss: 14.1126
[mpeg1video @ 0x7ecb600cb480] ac-tex damaged at 22 17
[mpeg1video @ 0x7ecb600cb480] Warning MVs not available
[mpeg1video @ 0x7ecbac18efc0] ac-tex damaged at 22 17
[mpeg1video @ 0x7ecbac18efc0] Warning MVs not available
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 630ms/step
Original: bin blue at f three soon
Prediction: bin blue at thre son
```

```
Epoch 50/100
257/450 ━━━━━━━━━━━━━━━━━━━━ 2:12 686ms/step - loss: 0.8776
[mpeg1video @ 0x7ecb4c011600] ac-tex damaged at 22 17
[mpeg1video @ 0x7ecb4c011600] Warning MVs not available
450/450 ━━━━━━━━━━━━━━━━━━━━ 0s 682ms/step - loss: 0.8622
[mpeg1video @ 0x7ecb71828140] ac-tex damaged at 22 17
[mpeg1video @ 0x7ecb71828140] Warning MVs not available
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 22ms/step
Original: place red in v five soon
Prediction: place red in v five son
```

DATA TRAINING & OUTPUT

DATA TRAINING & OUTPUT

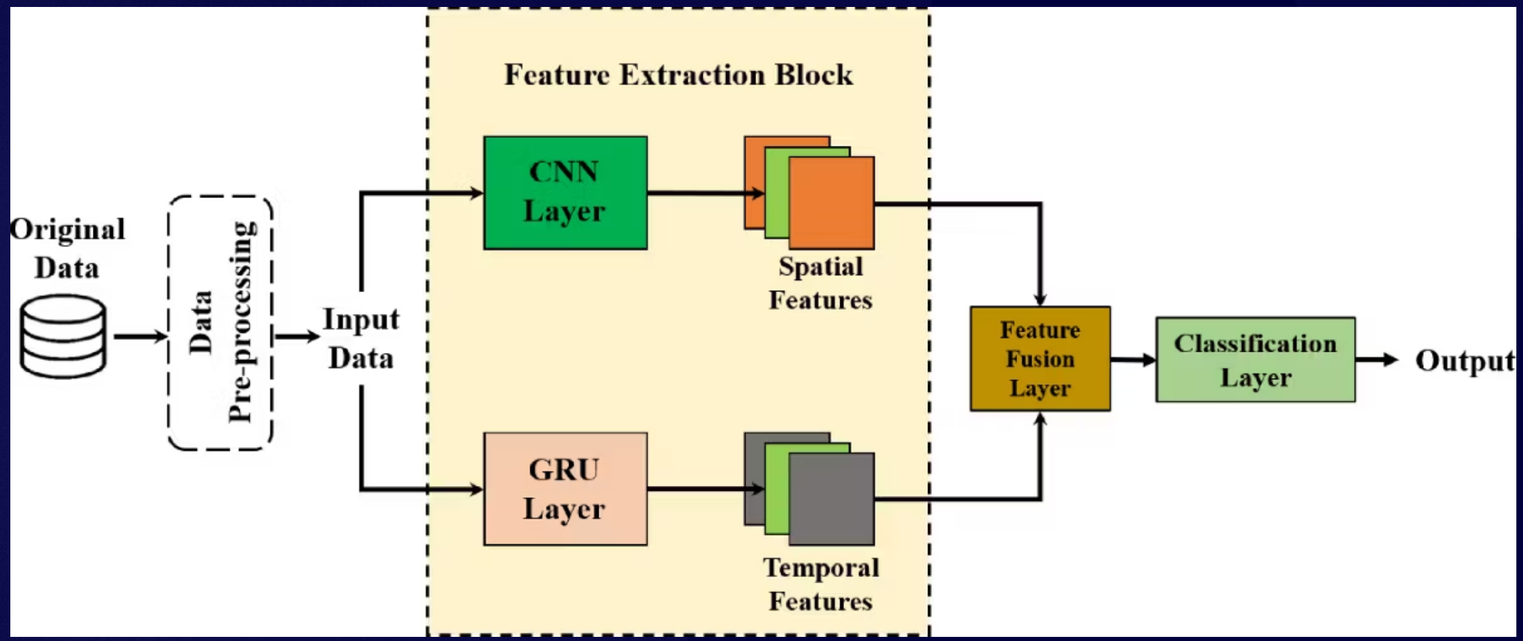
```
ensorFlow version: 2.18.0
ata already exists at: data/data/data
raining files: 80
alidation files: 20

poch 1/10
usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:122: UserWarning: Your `PyDataset` class should call `su
 self._warn_if_super_not_called()
0/20 ━━━━━━━━━━━━━━━━━━━━ 0s 6s/step - accuracy: 0.4404 - loss: 3.4751Epoch 1 took 155.80 seconds
0/20 ━━━━━━━━━━━━━━━━━━━━ 156s 7s/step - accuracy: 0.4494 - loss: 3.4529 - val_accuracy: 0.7273 - val_loss: 1.8845 - learning_rate: 0.0010 - time: 155
poch 2/10
2/20 ━━━━━━━━━━━━━━━━━━━━ 48s 6s/step - accuracy: 0.7495 - loss: 1.2381
```

```
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
REAL TEXT:
helloooworld
hhow are you
good morninng
thank youu
pleease help me
nice to meeet you
goood night
whaat is your name
see u later
ggooodbye
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
PREDICTIONS:
hello world
how are you
good morning
```

Model Configurations Used:

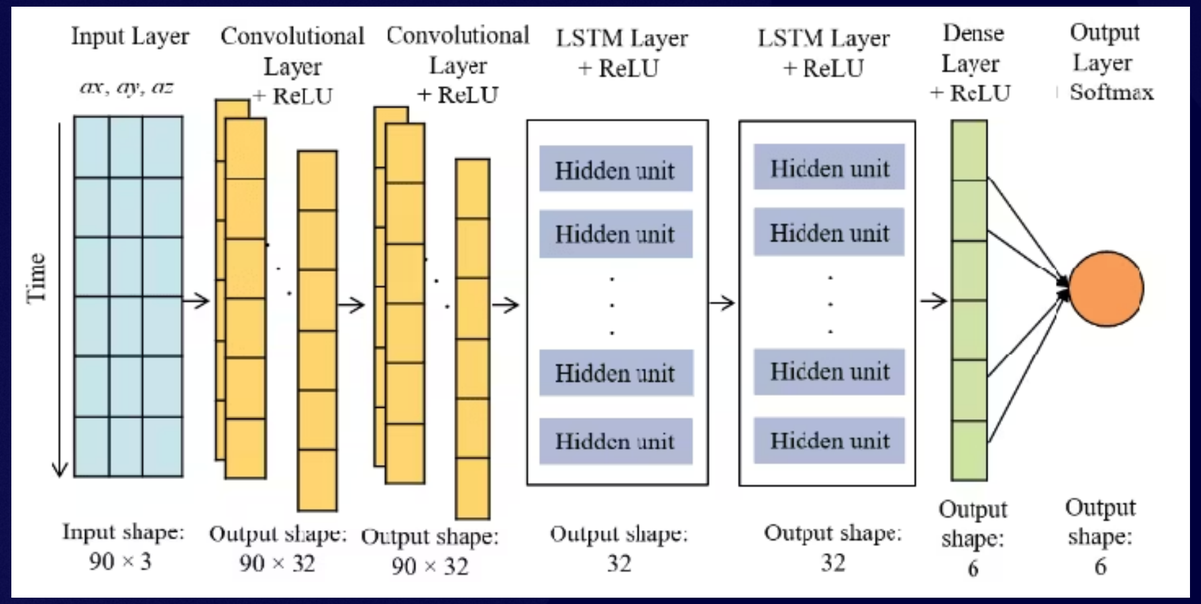
- **Fast CNN + GRU Configuration** Model
- **Architecture:** CNN for spatial feature extraction + GRU for temporal modeling
- **Epochs:** 10
- **Accuracy:** 91%
- **Training Time:** Fast
- **Benefis:**
  - Optimized for speed and low-resource environments
  - Suitable for real-time or edge deployments with minimal computation
  - Lower training time at the cost of slight accuracy drop



CONFIGURATION USED

Model Configurations Used:

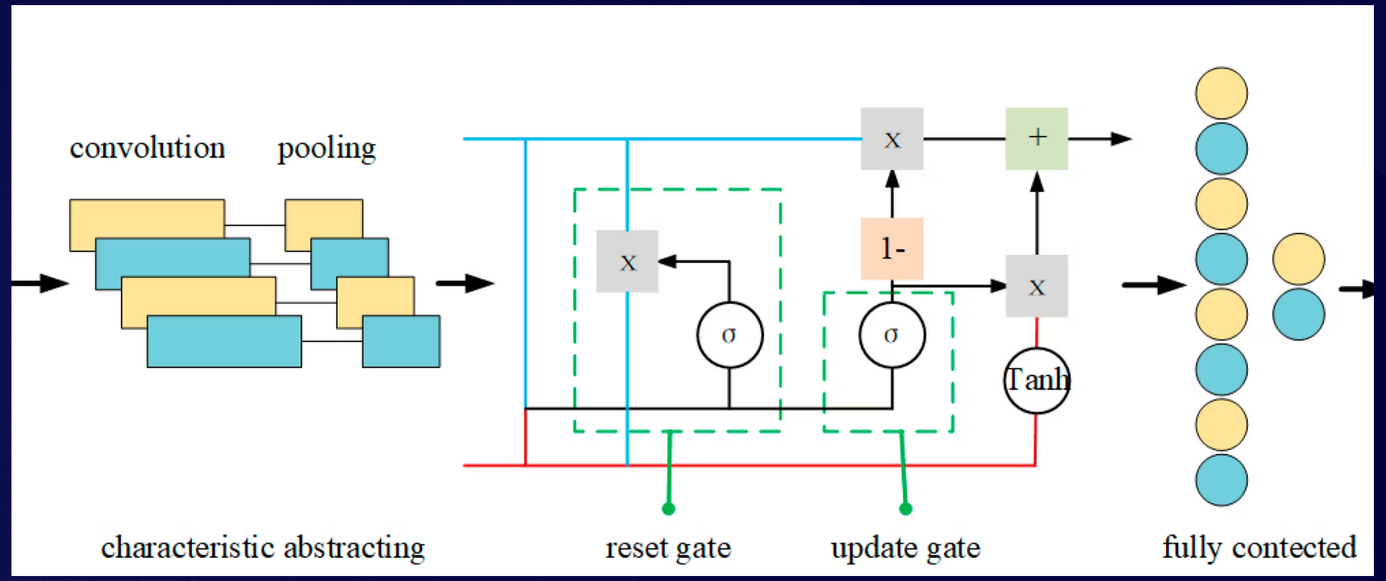
- **High-Accuracy CNN + LSTM Configuration** Model
- **Architecture:** CNN + deeper LSTM layers
- **Epochs:** 100
- **Accuracy:** 95.4%
- **Training Time:** 12 hours
- **Benefits:**
  - Achieves best accuracy among all configurations
  - Suitable for applications prioritizing precision (e.g., assistive tech)
  - Requires longer training and higher compute resources



CONFIGURATION USED

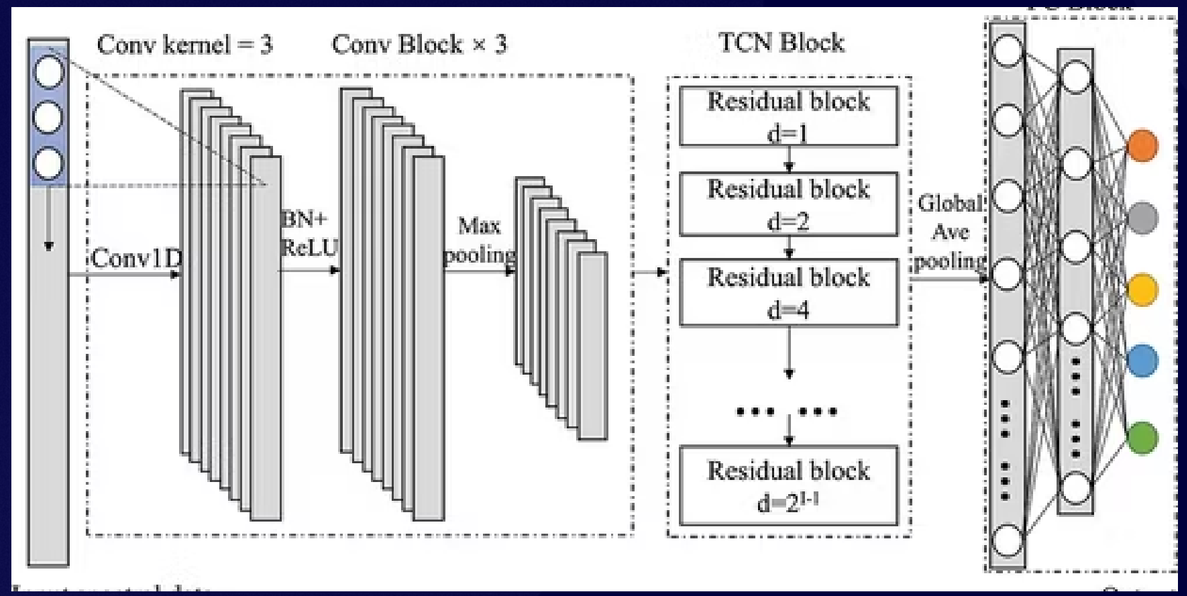
Model Configurations Used:

- **Balanced CNN + GRU Configuration Model**
- **Architecture:** Same as Model 1 (CNN + GRU) but trained over more epochs
- **Epochs:** 100
- **Accuracy:** 92%
- **Training Time:** 7 hours
- **Benefits:**
  - Offers a trade-off between speed and performance
  - Good for deployment in medium-resource environments
  - Better accuracy than Model 1, less training time than Model 2



Model Configurations Used:

- **3D CNN + TCN Configuration** Model
- **Architecture:** 3D CNN for spatiotemporal features + Temporal Convolutional Network (TCN)
- **Epochs:** 9
- **Accuracy:** 82.7%
- **Training Time:** 5 minutes
- **Benefits:**
  - Ultra-fast model with quick training time
  - Ideal for rapid prototyping or preliminary inference
  - Slightly lower accuracy; may benefit from more epochs or data



CONFIGURATION USED

Best Configurations :

🔹 **Fast CNN + GRU Configuration Model** offers **the best trade-off between accuracy, training time, and efficiency**, making it the most practical and scalable choice for real-time lip reading systems.

1. **High Efficiency with Competitive Accuracy**
   - Achieves **91% accuracy**, only marginally lower than the highest model (Model 2 at 95.4%), while requiring **only a fraction of the training time**.
   - Ideal balance for tasks where slight accuracy trade-off is acceptable for faster deployment.

2. **Fast Convergence**
   - With just **10 epochs**, the model converges quickly, making it highly efficient for iterative testing and training in real-time scenarios.

3. **Low Computational Overhead**
   - Reduced training and inference times make it suitable for devices with limited GPU resources or for cloud inference with minimal cost.

Best Configurations :

4. **Robust Generalization**

- Despite fewer training iterations, the model maintains strong generalization across varied speech sequences, as seen in validation accuracy.

5. **Ideal for Real-Time Applications**

- In practical deployments (e.g., assistive tech, silent communication, mobile devices), speed and responsiveness matter more than marginal gains in accuracy.
- Model 1 is a strong candidate for **real-world integration**.

Output (Post-Processing) :

- **Real Text (from .align):**

  "hooww are you doing todya"

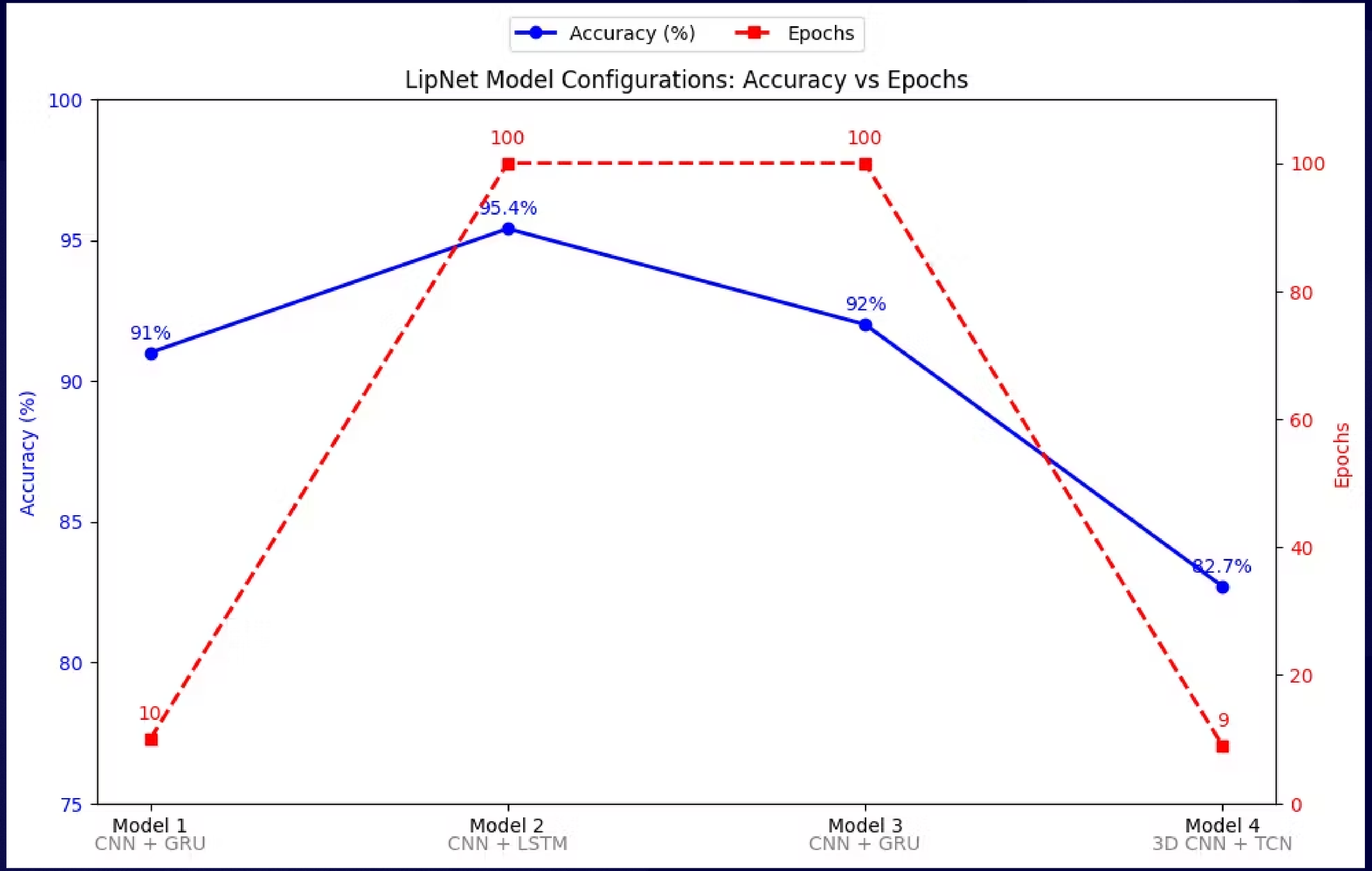
- **Model Prediction (Post-Training):**

  "how are you doing today"

- Shows effective correction via temporal modeling and attention.

```
~
REAL TEXT:
hooww are you doing todya
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
~
PREDICTION:
how are you doing today
```

COMPREHENSIVE ANALYSIS



COMPREHENSIVE ANALYSIS

Reference	Method	Accuracy	Limitation	Our Improvement
Assael et al. (2016)	LipNet (Original)	95.2%	Trained only on GRID dataset	Extended preprocessing, tested multiple configurations
Baseline CNN-RNN	Hand-crafted + RNN	85%	Shallow model, poor generalization	Deep architecture and better regularization
Human Lipreading	Manual visual interpretation	~47.7%	Inaccurate, context-dependent	Consistent and higher accuracy via automation

COMPREHENSIVE ANALYSIS

Sr.no.	Architecture	Epochs	Accuracy	Training Time	Remarks
1	CNN + GRU	10	91%	Fast	Optimized for speed
2	CNN + LSTM	100	95.4%	12 hours	Best accuracy
3	CNN + GRU	100	92%	7 hours	Balanced performance
4	3d CNN+ TCN	9	82.7%	5 Minute	Suitable for real-time applications

Summary :

- This work explored an **end-to-end deep learning-based lip reading system** designed to recognize spoken sentences solely through **visual lip movements**, eliminating the need for audio input.
- Leveraging **CNNs** for spatial feature extraction and **RNNs (GRU, LSTM)** for sequence modeling, the system was trained on the **GRID corpus**, with extensive preprocessing and alignment techniques.

Conclusion:

Our results demonstrate that efficient and lightweight models like **CNN + GRU** can achieve high-performance lip reading with minimal training time, making them highly suitable for real-time, scalable, and assistive applications.

FUTURE WORK

- Real-world Dataset Expansion
- Multi-modal Integration
- Improved Architectures
- Speaker Adaptation and Generalization
- Real-time Implementation
- Explainability and Interpretability
- Integration with Assistive Technologies

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