Writer Verification on Multi-Language Script using Deep Learning

Project by
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Next Presenter: Sharanya Saha

Motivation, Software Used, Hardware Used, Significance of Hardware

Motivation

- Shortage of Research in Native Indian Language Recognition
- Authentication of Manuscripts
- Forensic Analysis and Law Enforcement
- Plagiarism Verification

Software Used

- Python 3.8
- TensorFlow 2.0
- Keras
- NumPy
- Pandas
- Matplolib
- SeaBorn

Hardware Used

- HP Pavilion with 2.7GHz Quad-Core Intel i5, Integrated Graphics Card, 8GB RAM
- Dell G3 with 2.6GHz Hexa-Core Intel i7 Processor, Integrated Graphics Card, 8GB RAM
- Asus Vivobook 2GHz Quad-Core AMD Ryzen 5 Processor, Integrated Graphics Card, 8GB RAM

Significance of the Hardware

- RAM and Processor for Processing Speed
- GPU Might Help!

- Cloud Platforms is a great alternative!

Next Presenter: Rahul Roy

Background, Summary of Present Work, Our Contribution

Background

- Works on Image Recognition and CNN
  - ImageNet classification with deep Convolutional Neural Networks [1]
  - Very Deep Convolutional Networks for Large-Scale Image Recognition [2]
- Works on Character Recognition
  - Automatic Visual Features for Writer Identification: A Deep Learning Approach [3]
  - Handwritten Character Recognition of South Indian Scripts: A Review [4]
  - A High Performance Domain Specific Ocr For Bangla Script [5]
  - Bangla character recognition based on Mobilenet v1 and Inception v3 [6]
  - CNN implementation based on Bangla numeral character recognition [7]
- Works on Writer Recognition
  - Offline writer identification using convolutional neural network activation features [8]
  - Writer identification using an HMM-based handwriting recognition system: To normalize the input or not [9]
  - Offline Text-Independent Writer Identification Based on Scale Invariant Feature Transform [10]

Summary of Related Work

- Lack of Work specific to Bangla

Reference	Year	Model	Type	Dataset	Result (%)
Adak et al. [11]	2019	VGG16	Verification	Self Procured	97.77
Christlein et al. [8]	2015	CNN (Super Vector encoded)	Identification	Self Procured	88.60
Schlapbach et al. [9]	2006	Hidden Markov Model	Identification	Self Procured	63.12
Wu et al. [10]	2014	SDS + SOH	Identification	Multiple	99.2

Table 1. Type of Work

Our Contribution through Present Work

- Writer verification
- Verification on Word Level Features
- Percentage of Similarities with the author
- Unique Dataset with 100+ volunteers

Next Presenter: Souporno Ghosh

About Data Set, About VGG16

Collection of Data Set

- 100+ volunteers
- 2 Language: English, Bangla
- Handwritten Passage
- Passages scanned into images

Preparation of Data Set

- Data Segmented into Word-Sized Images [12]

Data Set Organisation

- Each Dataset has 20 Subsets
- Every Subset has Data for one Writer; Another writer for verification
- Number of writers: 100 for Bangla, 101 for English
- 5 Sets of Data for Each Author
- 3 Training Sets and 2 Testing Sets
- Average 43 images per Set
- Tag Image File Format
- Format: <Writer Code>_<Set Number>_<Image Number>

Example Data

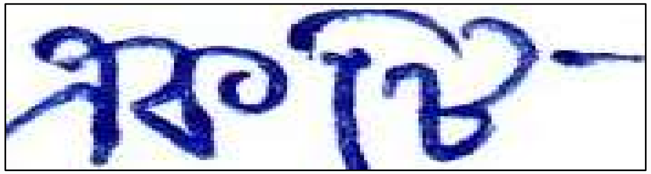


Fig 1. 0000_01_0.tiff

Organization of Extracted Feature Set

- Extracted features stored as CSV files
- <Language code> added to the stored feature matrix
  - Language Code for Bangla: 11
  - Language Code for English: 00
- CSV File Name Format: <Writer Code>_<Language Code>_<Set Number>

About VGG16 Model

- Proposed by Simonyan and Zisserman in 2014 [2]
- 92.7% accuracy with the ILSVRC subset of ImageNet Database
- 1^{st} and 2^{nd} place in ILSVRC 2014
- VGG = Visual Geometry Group
- 16 Neural Network Layers
  - 13 Convolutional Networks
  - 3 Dense Networks
- Takes 224 x 224 pixel Images with RGB as an Input

Benefits of VGG16

- Very accurate
- Simple and Uniform
- Popular

Challenges of VGG16

- Slow to Train
- Huge Weights

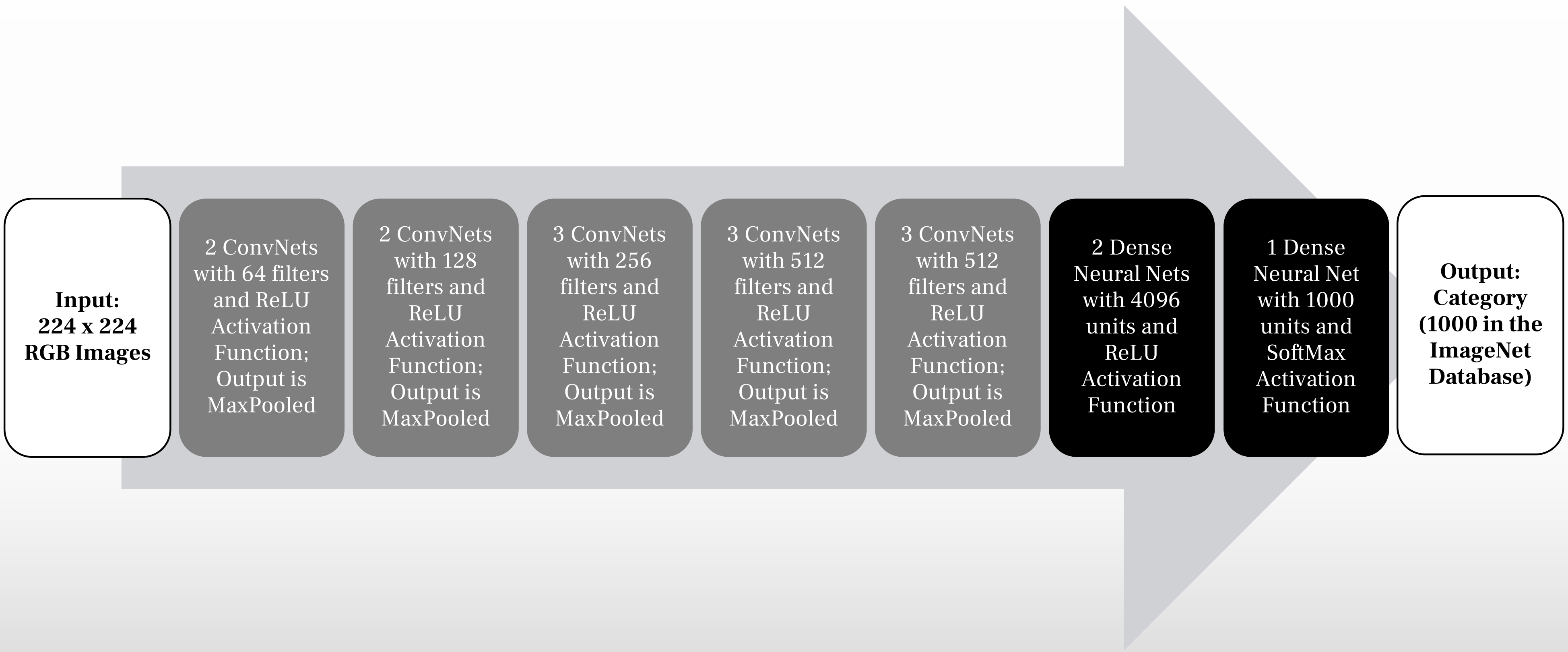
Next Presenter: Soumya Nasipuri

Architecture of VGG16, Feature Extraction, What Comes Next

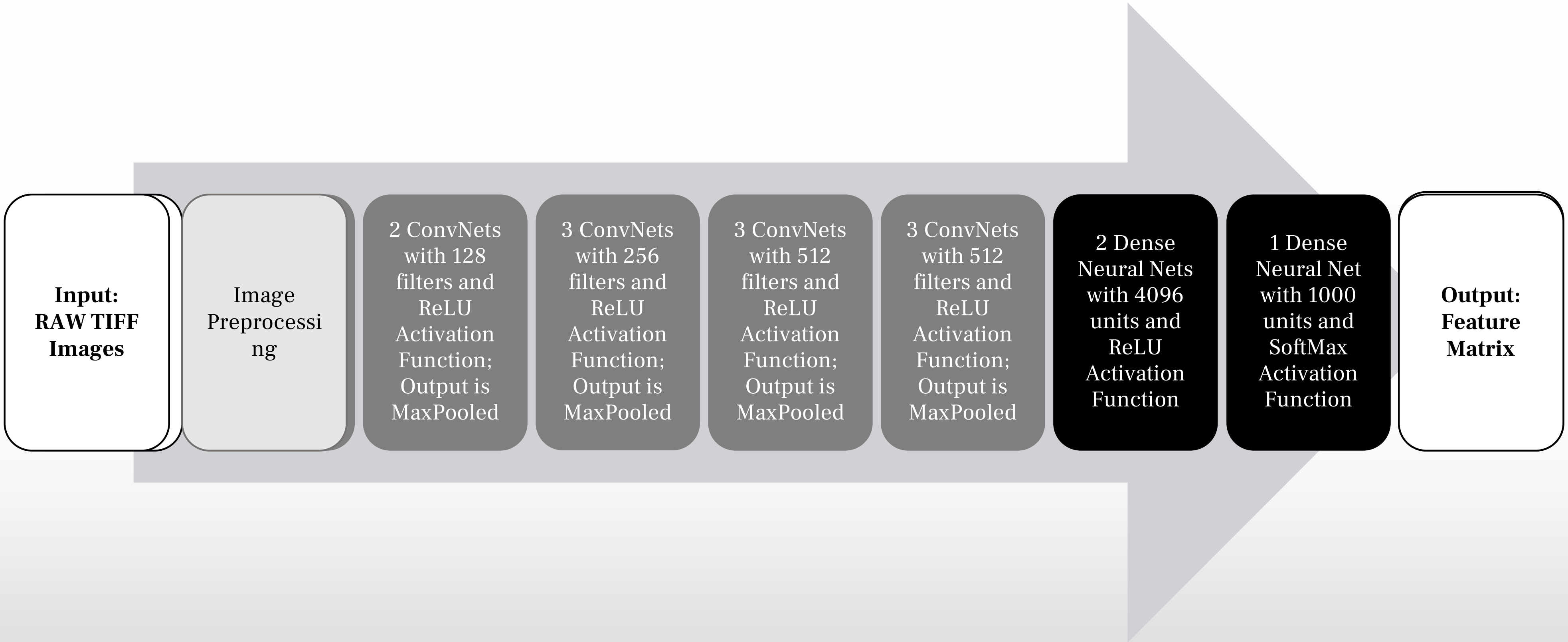
Image Pre-processing

Raw Tiff Images → Normalisation → Resizing → Expansion of dimensions from 3D array to 2D array → 224 x 224 RGB Image

Architecture of VGG16 Model



Feature Extraction



Extracted Features

- Dimensions: 4096 x 1 per image
- Consolidated Features for each Set of Images
- 5 sets of extracted features for each author
- Dimensions for Each Extracted Feature Matrix for a Set: 4096 x r
  - r = number of rows = number of images in each set
- Feature extraction time = 2 hours 14 minutes 17 seconds (approx.)

Handwriting Verification:

- Updated the last layer of VGG16 Model
- Trained the model with every writer pair
- Distinguish between the handwriting of the primary writer pair and the other writer pairs.

Last layer of VGG16

- Relu and softmax
- Adam optimizer is used
- Batch size is 32
- The model is stored as a .h5 file

Additional Models

- ResNet
- AlexNet

In both the models, the output size were reduced to two from their original.

Next Presenter: Sharanya Saha

Accuracy, Conclusion, References

Accuracy

Final Accuracy: The average accuracy of the obtained accuracies

Model	Final Accuracy
VGG 16	62.75%
ResNet	72.09%
AlexNet	74.45%

Table 2. Comparing accuracies of different models

VGG-16

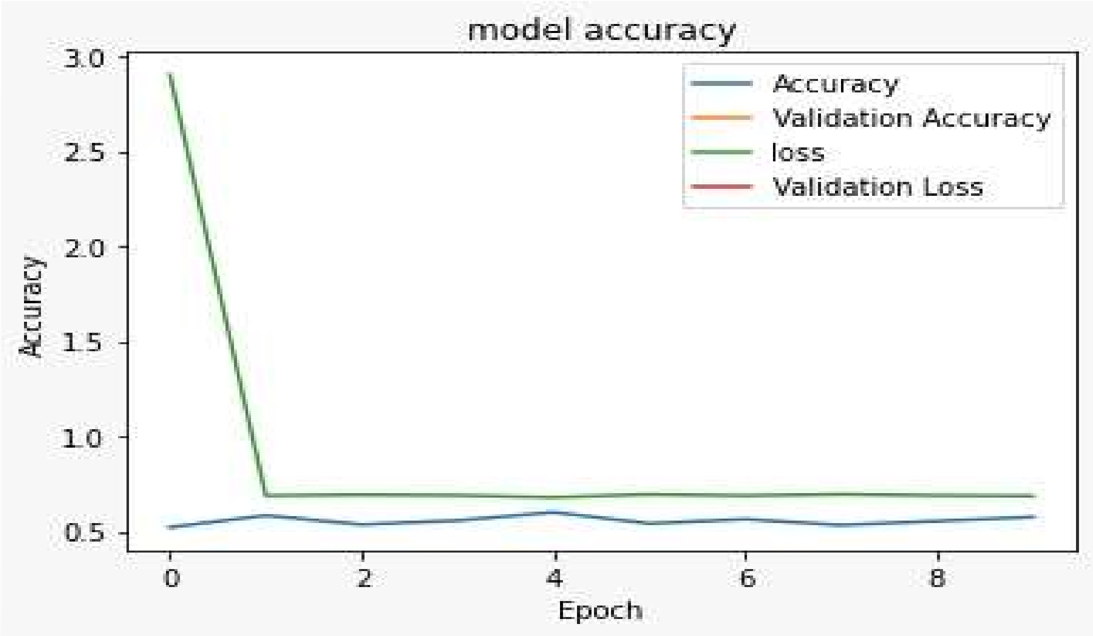


Fig 2. Graph depicting accuracy, validation accuracy, loss and validation loss over multiple epochs

ResNet

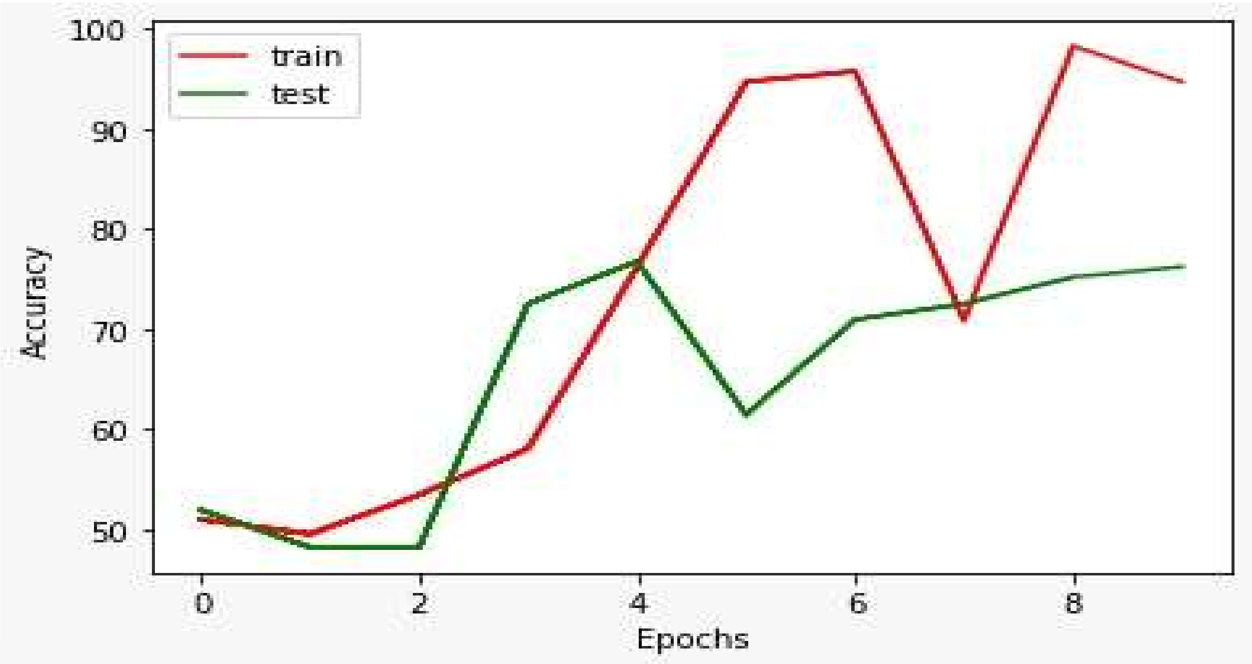


Fig 3. Graph depicting accuracy, validation accuracy, loss and validation loss over multiple epochs

AlexNet

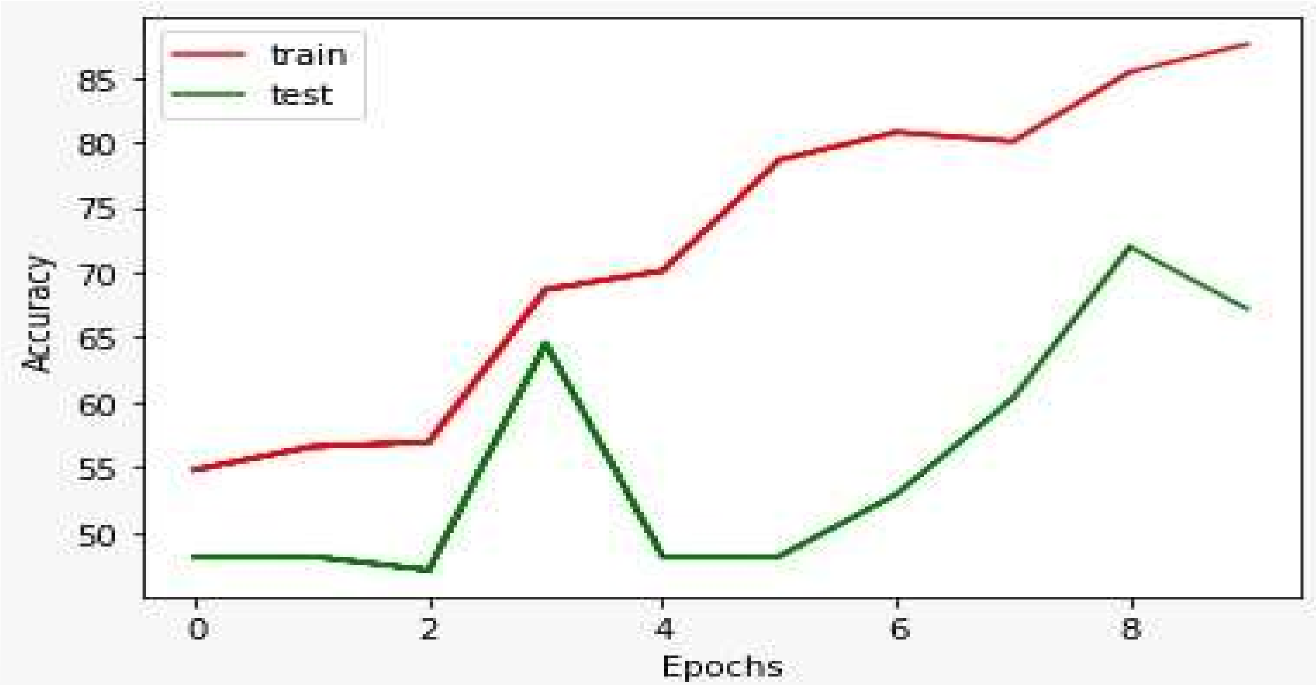


Fig 4. Graph depicting accuracy, validation accuracy, loss and validation loss over multiple epochs

Conclusion

	Adak et al.	Present Work
Year	2019	2021
Model	VGG16	VGG16
Type	Verification	Verification
Accuracy achieved	97.77%	62.75%

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Thank You