Center for Research in Intelligent Systems

UCR

Latent Fingerprint Image Quality Assessment Using Deep Learning

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Outline

- Problem Definition
- Related Work
- Technical Approach
- Experiments and Results
- Performance Evaluation
- Conclusions

Problem Definition

- Latent fingerprints – Impressions unintentionally left on surfaces

Good Bad Ugly

(a) G070L2 (b) B122L4 (c) U292L1

- Examiner Assignments:
  - Value for individualization (VID)
  - Value for exclusion only (VEO)
  - No value (NV)

- Need automated value determination to eliminate inconsistency and subjectivity inherent in manual feature markups

- For example: Incorrect NV determination could result in missed opportunity to identify a crime suspect

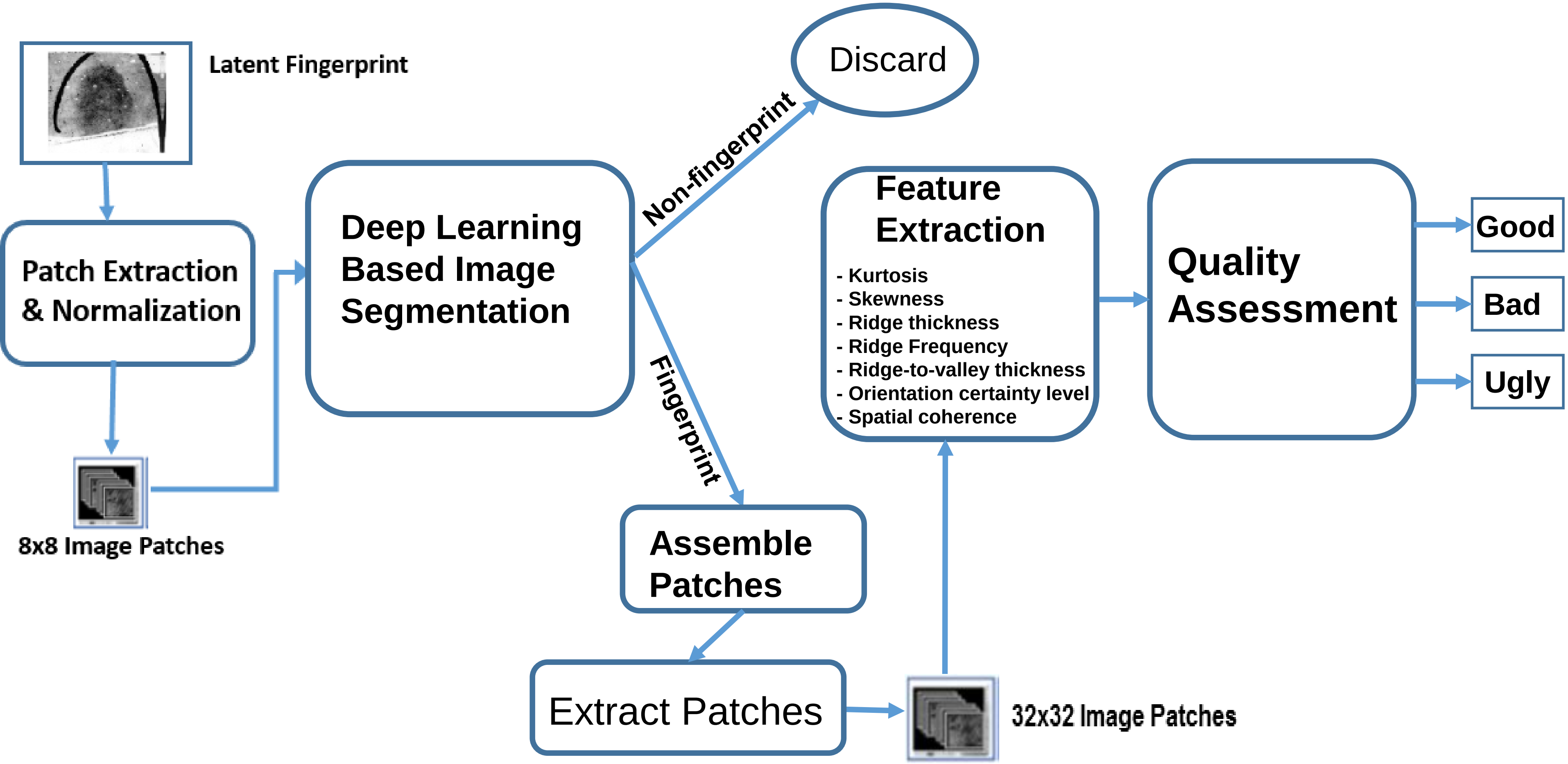
Related Work

Author	Principle	Comments
Yoon et al. (BTAS'13)	Ridge clarity, Minutiae reliability and count, Ridge connectivity, Finger position	Manually annotated minutiae
Sankaran et al. (BTAS'13)	Ridge clarity, Ridge quality features	Manually annotated minutiae, Manually marked ROI
Cao et al. (ICB'16)	Minutiae count, Ridge clarity, Ridge flow features	Manually marked ROI
Chugh et al. (TIFS'18)	Crowdsourcing based framework and multidimensional scaling, with quantitative prediction model	Manually marked ROI

Contributions of this paper:

- Latent fingerprint Quality assessment is posed as a classification problem
- Proposes a region-of-interest based latent quality assessment strategy that requires no manual intervention or feature markups

Proposed Framework



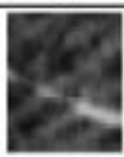
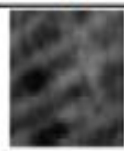
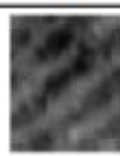
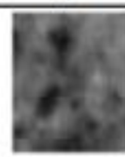
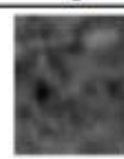
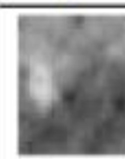
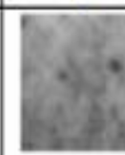
- 7-Layer Deep learning network for segmentation
- 3-Layer Perceptron network for quality assessment

Ground-Truth Generation

- Partition the segmented fingerprint into 32x32 non-overlapping patches
- Label Patches:

$$L_p = \begin{cases} 1, & \text{if } \tau > 1.75 \text{ and } \kappa < 0.65; \\ 2, & \text{if } 1.65 < \tau < 1.75 \text{ and} \\ & \quad 0.65 < \kappa < 0.70; \\ 3, & \text{if } \tau < 1.70 \text{ and } \kappa > 0.70. \end{cases}$$

where τ and κ are the average fractal dimension and fractal dimension spatial frequency, respectively.

1	2	3	4	5	6	7	8	9	10	11
Image Patch										
FD_{av}	1.773	1.804	1.767	1.675	1.737	1.727	1.590	1.633	1.645	1.512
FD_{sf}	0.611	0.617	0.649	0.669	0.675	0.659	0.713	0.772	0.768	0.825

Good

Bad

Ugly

Training, Validation, Testing

- 10,000 32x32 (7,000 for training, 1,500 for validation and 1,500 for testing) patches from 88 Good, 85 Bad and 85 Ugly ROIs
- Compute features from the patches

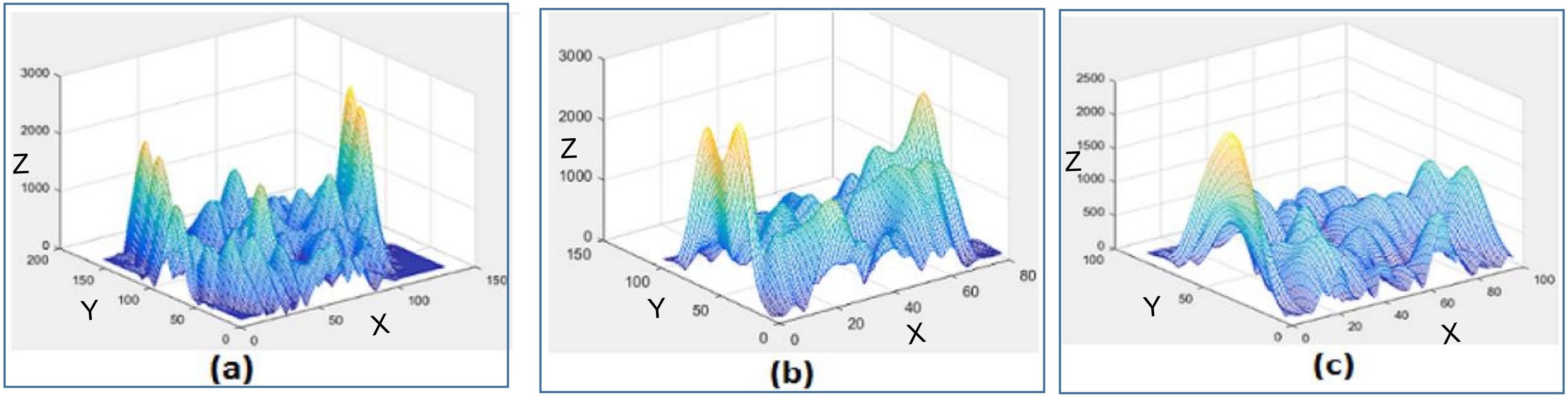
- Train a multi-class perceptron classifier with features

$$Q(L) = \begin{cases} 1, & \text{if val} = \text{g}; \\ 2, & \text{if val} = \text{b}; \\ 3, & \text{if val} = \text{u}. \end{cases}$$

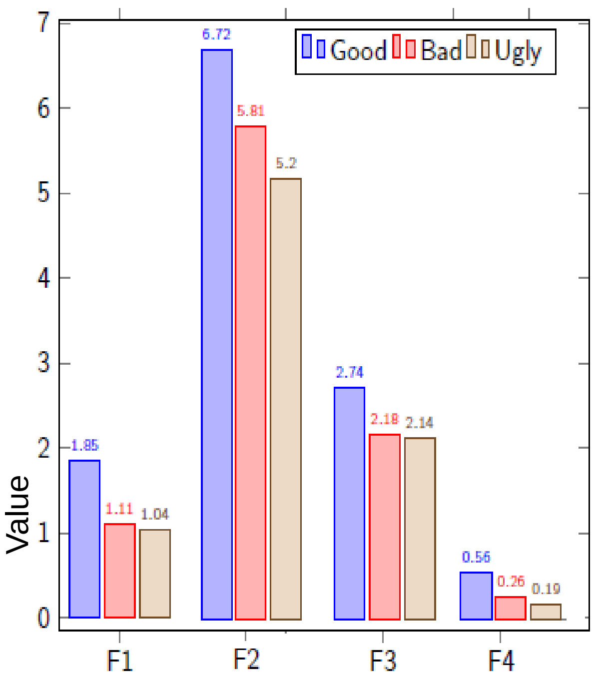
where *L* is segmented latent fingerprint, *g, b, u* are the number of patches of *L* classified as Good (1), Bad (2), or Ugly (3), respectively, and *val* = *max(g, b, u)*

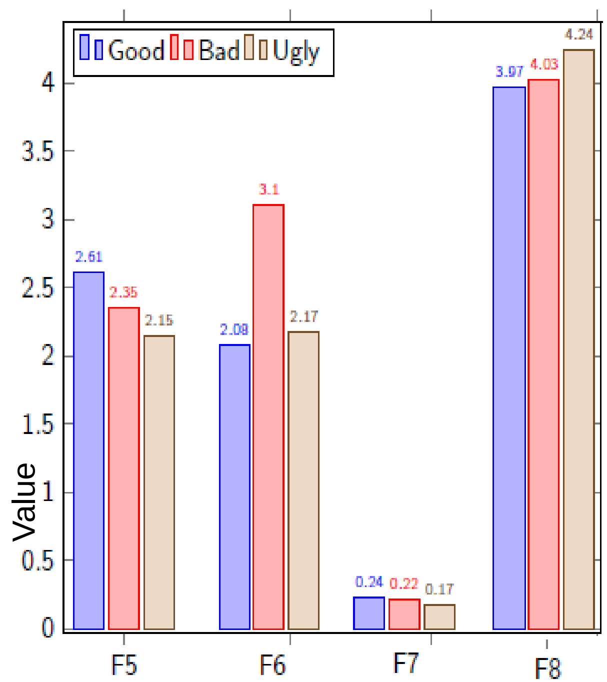
- Ties are broken optimistically: If *g*=*b* and *b*>*u, Q(L)* = Good

Features for Quality Assessment



Gabor magnitude responses to sample segmented fingerprints : (a) Good (b) Bad, and (c) Ugly





F1 - Peak skewness of magnitude response
F2 - Peak kurtosis of phase response
F3 - Mean kurtosis of magnitude response
F4 - Mean skewness of magnitude response
F5 - Mean kurtosis of phase response
F6 - Peak skewness of phase response
F7 - Mean skewness of phase response
F8 - Peak of magnitude response

Note: F7 was scaled up by **0.2** for visibility

Network Parameters

Segmentation Network

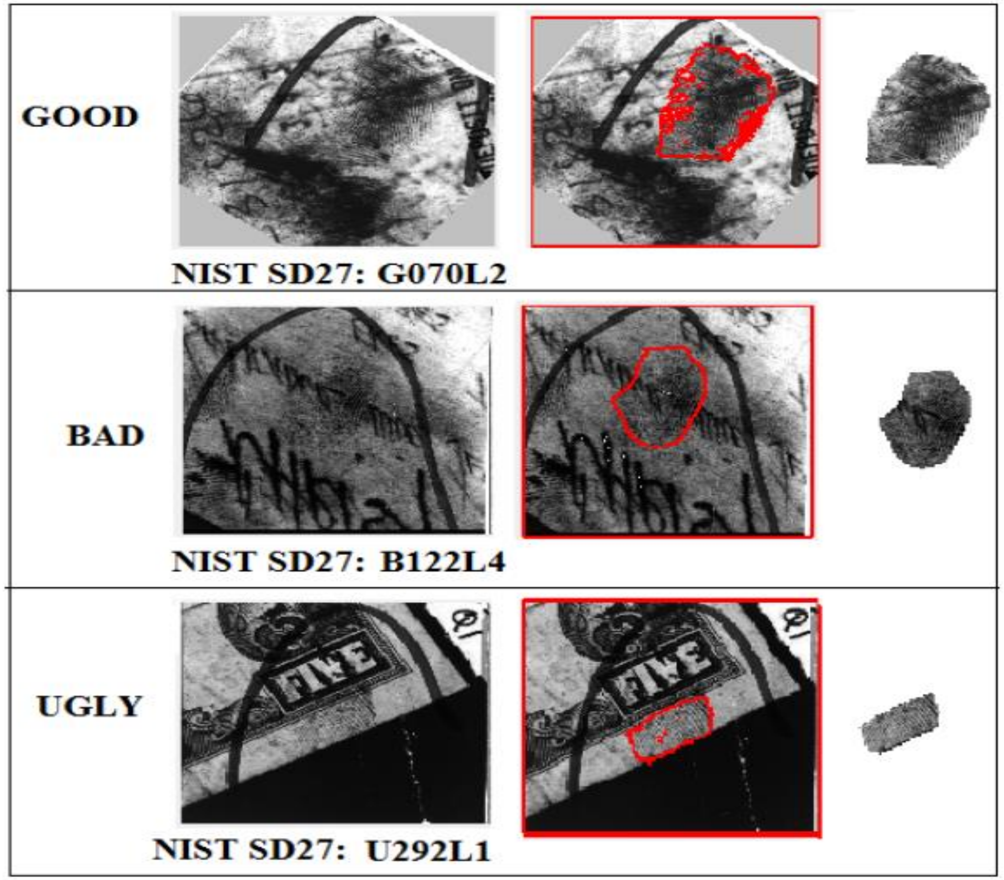
Parameter	L_1	L_2	L_3	L_4	L_5	L_6	L_7
Number of Neurons	64	800	1000	1200	1024	1024	2
Batch Size	-	100	100	100	100	100	-
Epochs	-	50	50	50	50	-	-
Learning Rate	-	1e-3	5e-4	5e-4	5e-4	5e-4	-
Momentum	-	0.70	0.70	0.70	0.70	0.70	-
Iteration	-	-	-	-	-	50	-

Quality Assessment Network

Parameter	*Input Layer*	*Hidden Layer*	*Output Layer*
Number of Neurons	1024	450	3
Batch Size	-	32	-
Epochs	-	10	-
Transfer function	-	logsig	tansig

Results - Segmentation

- Database - NIST SD27 (88 Good, 85 Bad, 85 Ugly latents)
- 232,000 8x8 patches (132,000 for training, 50,000 for validation and 50,000 for testing) with 40% from Good, 30% from Bad, and 30% from Ugly



Visual Segmentation Results

		Predicted Patch Class (Training)	
		Fingerprint	Non-Fingerprint
Actual Patch Class	Fingerprint	23,665	11
	Non-Fingerprint	0	108,324

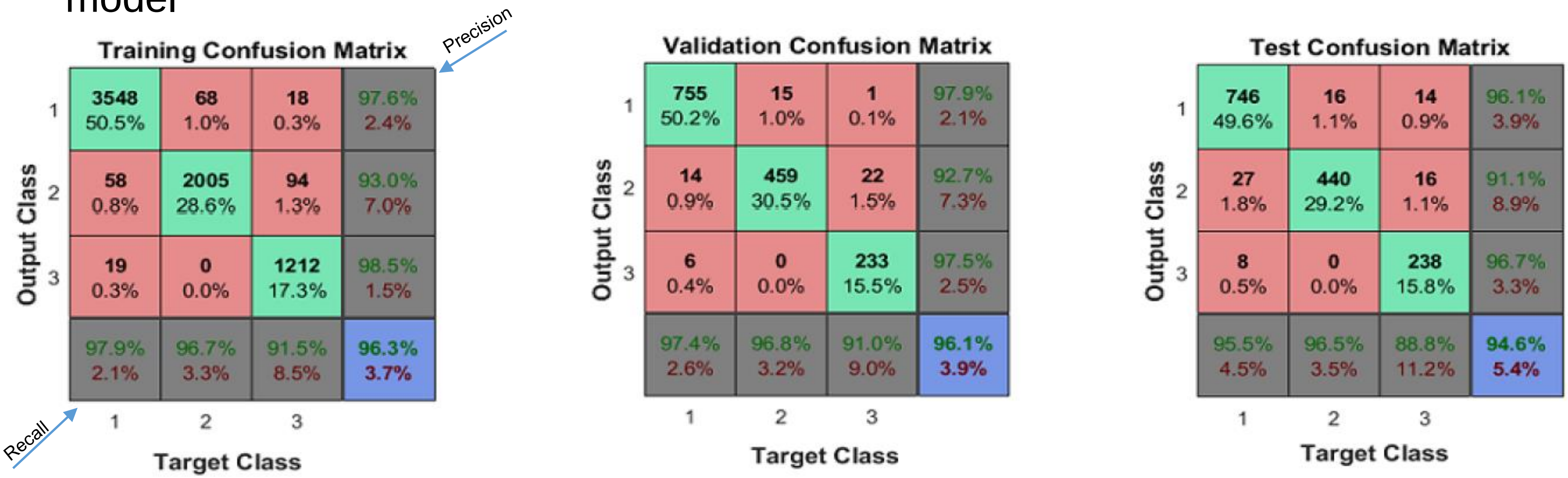
		Predicted Patch Class (Validation)	
		Fingerprint	Non-Fingerprint
Actual Patch Class	Fingerprint	13,637	163
	Non-Fingerprint	2	36,198

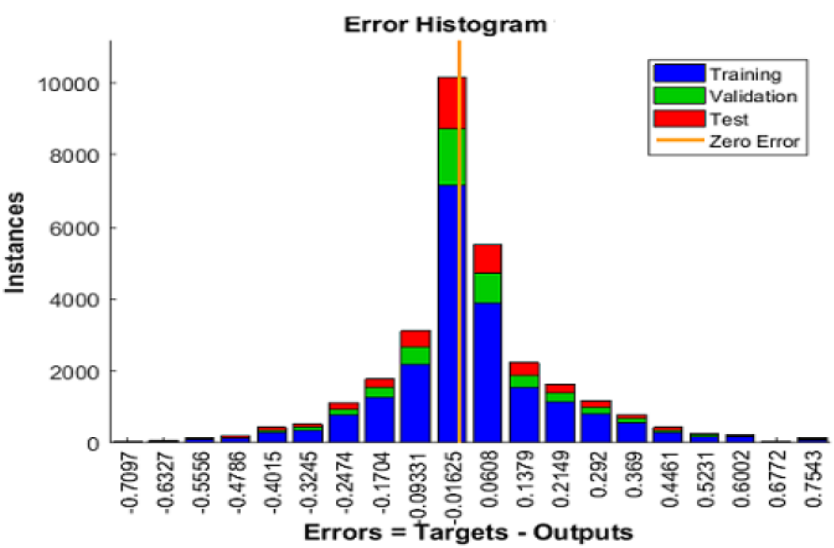
		Predicted Patch Class (Testing)	
		Fingerprint	Non-Fingerprint
Actual Patch Class	Fingerprint	13,914	188
	Non-Fingerprint	5	35,893

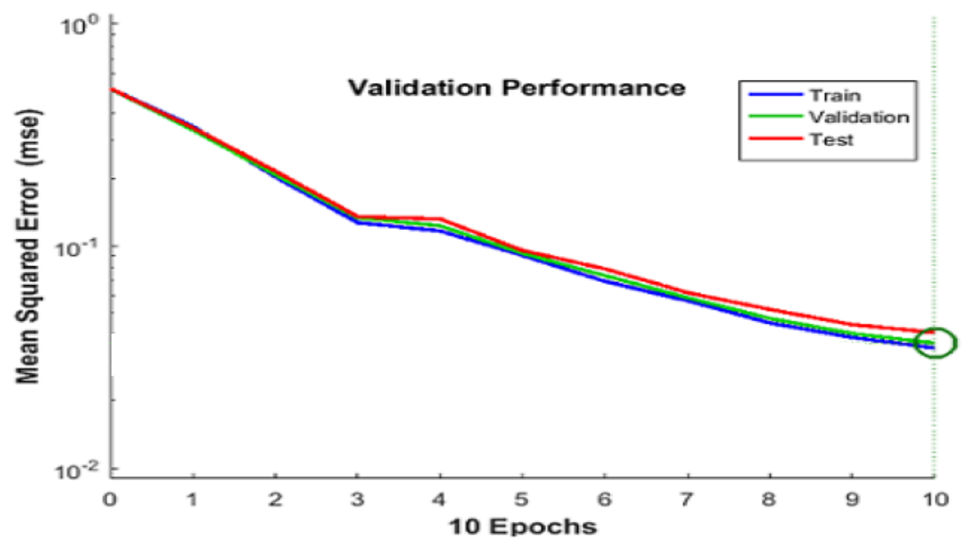
Confusion Matrices:
Training, Validation & Testing

Results – Quality Assessment

- Three confusion matrices showing the performance of the quality assessment model







Evaluation of Quality Prediction

- The VID, VEO, and NV Rank-1 retrieval rates for the 258 latents in NIST SD27 with state-of-the-art latent AFIS using quality value predictions

Author	VID	VEO	NV
Latent examiners [Hicklin et al.] *Journal of Forensic Identification, 2011*	155/210	**11**/41	0/7
Expert Crowd [Chugh et al.] *IEEE Transactions on Information Forensics and Security, 2018*	161/210	5/41	0/7
This Work	**164**/210	4/41	0/7

Conclusions and Future Work

- Automatic region-of-interest based latent fingerprint quality assessment using deep learning.
- Latent quality determined by classifying its ROI 32x32 patches into Good, Bad or Ugly bins.
- Comparative analysis on NIST SD27 shows that the proposed approach performs better than the state-of-the-art latent fingerprint quality assessment model.
- Use NIST Finger Image Quality (NFIQ 2.0) as a baseline for mapping latent fingerprint quality assessment to recognition performance.