

SECURE FINGERPRINT AUTHENTICATION USING DEEP LEARNING AND MINUTIAE VERIFICATION

Jhanvi Shah, Yagnik Poshiya, Adnan Vahora

Problem Definition

Fingerprint authentication has become a norm in our day-to-day society and its vulnerability is never challenged. However, due to technological advancements, malicious attempts which bypass security systems using fake fingerprints have increased. Many systems today use algorithms that match the records in the database with the input provided by the scanner for user authentication. As these methods in specific applications are not modified and updated regularly at a pace that equals or exceeds the progress made by malicious individuals, it leaves biometric recognition at an increased risk and makes them susceptible to cyber-attacks.

Project Purpose

In this project, there are two operating modes for the biometric system. The first, and simplest mode, is called pre-verification. Here in this mode, the first image is classified into two categories either real or fake based on some fingerprint features. If the input image will be real then the system provides that image to the identification phase and if the image will be fake then the system stops the further process of giving access to a particular person. Using the pre-verification phase system security will be increased. Because it verifies that it is not a spoof image. In the identification phase, subject id and finger number will be predicted and fingerprint matching is performed based on detailed level minutiae features. And if the prediction probability is higher than 91% and if the system will find best match with stored template then and then system will give access to that particular user.

Data Resource

Scanner	Model	Resolution [dpi]	Image [px]	Format
Green Bit	DactyScan26	500	500*500	PNG
Biometrika	HiScan-PRO	1000	1000*1000	BMP
Digital Persona	U.are.U 5160	500	252*324	PNG
Crossmatch	L Scan Guardian	500	640*480	BMP

Table 1: Fingerprint Scanner Characteristics

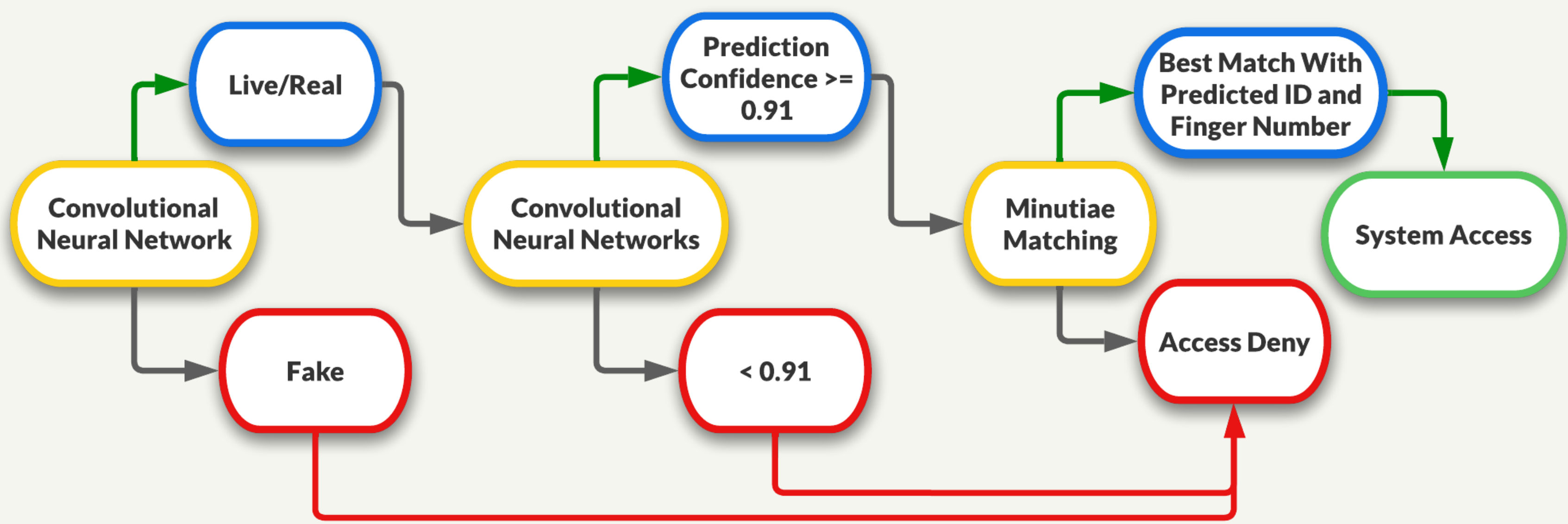
Dataset	Live Image	Ecoflex	Gelatine	Latex	Woodglue	Liquid Ecoflex	RTV
Green Bit	1000	250	250	250	250	250	250
Biometrika	1000	250	250	250	250	250	250
Digital_Persona	1000	250	250	250	250	250	250
	Live Image	Body Double	Ecoflex	Playdoh	OOMOO	Gelatine	---
Crossmatch	1500	300	270	281	297	300	---

Table 2: Number Of Images For Each Testing Set In LivDet 2015 Database

Category	Real	Altered-Easy	Altered-Medium	Altered-Hard	Total
Total Images	6000	17981	17077	14330	55388
Images Used In Train-Test Process	6000	0000	17077	14330	37407

Table 3: SOCOFing Dataset Information

Biometric System



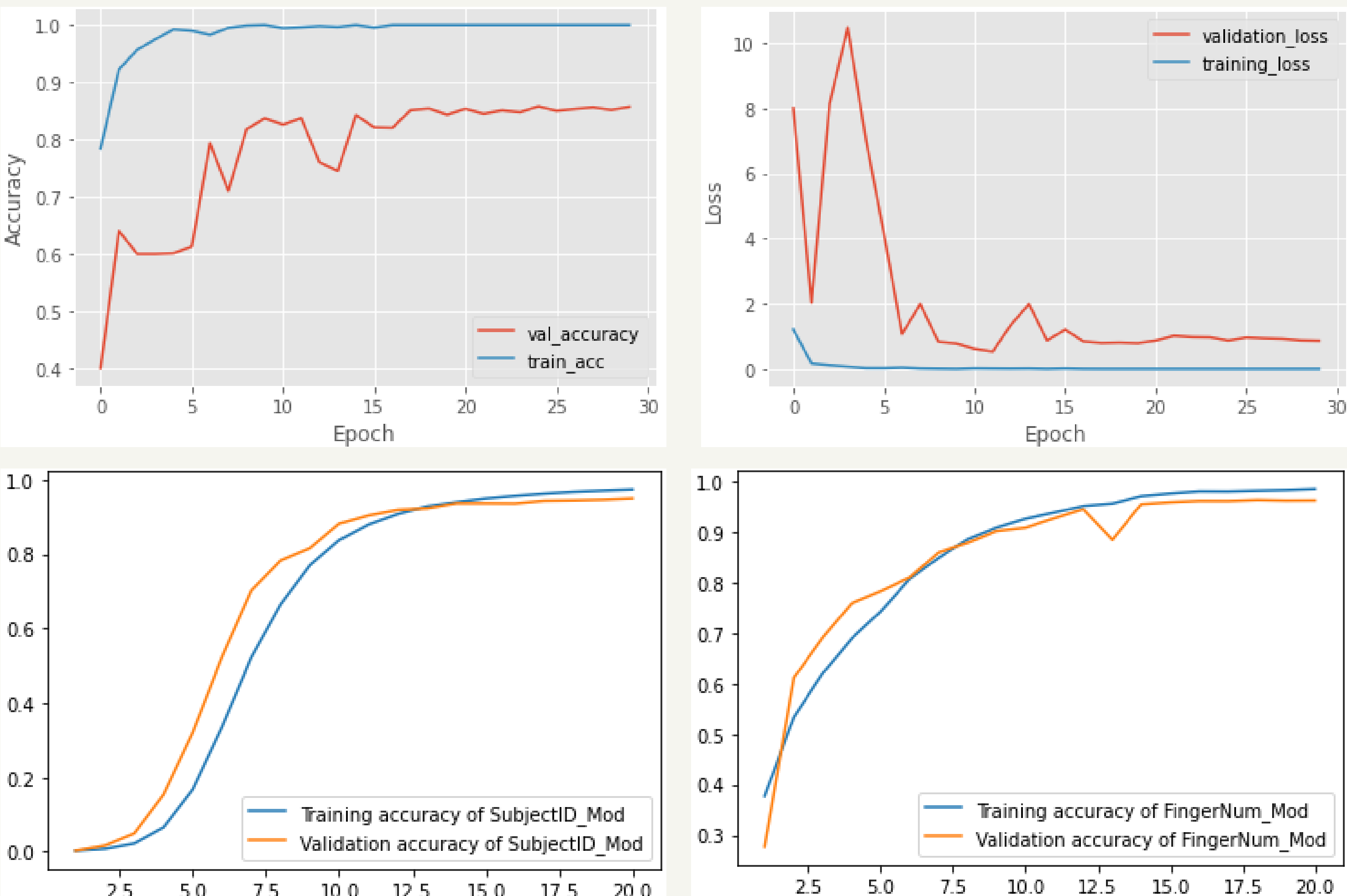
Layer	Type	Output Shape	Parameters
conv2d	Conv2D	(None,126,126,32)	896
batch_normalization	BatchNormalization	(None,126,126,32)	128
max_pooling2d	MaxPooling2D	(None,63,63,32)	0
conv2d_1	Conv2D	(None,61,61,64)	18496
batch_normalization_1	BatchNormalization	(None,61,61,64)	256
max_pooling2d_1	MaxPooling2D	(None,30,30,64)	0
conv2d_2	Conv2D	(None,28,28,64)	36928
batch_normalization_2	BatchNormalization	(None,28,28,64)	256
max_pooling2d_2	MaxPooling2D	(None,14,14,64)	0
flatten	Flatten	(None,12544)	0
dense	Dense	(None,256)	3211520
dense_1	Dense	(None,1)	257

Table 4: CNN Model For Pre-verification Phase

Layer	Type	Output Shape	Parameters
conv2d	Conv2D	(None,92,92,32)	896
batch_normalization	BatchNormalization	(None,92,92,32)	128
max_pooling2d	MaxPooling2D	(None,46,46,32)	0
conv2d_1	Conv2D	(None,42,42,64)	51264
batch_normalization_1	BatchNormalization	(None,42,42,64)	256
max_pooling2d_1	MaxPooling2D	(None,21,21,64)	0
conv2d_2	Conv2D	(None,19,19,128)	73856
batch_normalization_2	BatchNormalization	(None,19,19,128)	512
max_pooling2d_2	MaxPooling2D	(None,9,9,128)	0
dropout	Dropout	(None,9,9,128)	0
flatten	Flatten	(None,10368)	0
dense	Dense	(None,256)	2654464
dropout_1	Dropout	(None,256)	0
dense_1	Dense	(None,600/10)	154200/2570

Table 5: CNN Models For Matching Phase

Experimental Results



Conclusion

So many different-different architectures were applied on LivDet 2015 database but the given architecture of the CNN model for pre-verification phase outperformed among them with 85.68% validation accuracy. In fingerprint matching phase, the subjectID model performed well with 97.34% training accuracy, 98.98% testing accuracy and the fingerNum model also performed well with 98.56% training accuracy, 99.23% testing accuracy on SOCOFing dataset.