5.6 Summary and Conclusion

This chapter discussed the experimentation carried out to optimize and train the three machine learning techniques and the experimentation carried out to evaluate the classification accuracy and speed of the three techniques. These experiments ultimately yielded clear answers to the three research sub-questions set out in Chapter 1.

At this stage, it is possible to provide an answer to the main research question which was posed as follows: "How do Support Vector Machines, Artificial Neural Networks and Random Forests compare in the context of SASL hand shape recognition?".

In response to this question, it is stated that the SVM is considerably quicker to optimize and train that the ANN and RF, the ANN is more accurate and consistent than the SVM and RF, given a trained and optimized classification model, and the RF is considerably faster when it comes to classifying a single input image, given a trained and optimized classification model, than the ANN and SVM.

A detailed analysis and discussion of the results culminated in the selection of the ANN machine learning technique as the best technique for SASL hand shape recognition, as compared to the SVM and RF. The motivation for this choice was the fact that it achieves a higher and more consistent accuracy than both other techniques and has a classification time that is comparable to that of the RF. While the optimization and training time was considerably higher than that of the SVM, this is a once-off cost that can definitely be worth it, given the final classifier is more accurate and much faster.

It was also found that the classification accuracy result obtained by Li using a completely different dataset to the one used in this research was very close to the classification accuracy achieved by the SVM in this research. This demonstrates the robustness and accuracy of the framework, and demonstrates that the feature extraction procedure was re-implemented correctly in this research.

The next chapter concludes the thesis.

Chapter 6

Conclusion

This research aimed to compare the use of Support Vector Machines (SVMs), used extensively in the SASL research group [2, 12, 44, 45, 69], with other promising machine learning techniques, in this case Artificial Neural Networks (ANNs) and Random Forests (RFs) in the context of SASL hand shape recognition. Four factors were considered in this comparison, namely: classification accuracy which is the most important factor, classification speed which is the second-most important factor, and the time required to optimize and train the technique, which are both very important, but not as important as the two previous factors.

In response to the first research sub-question posed as “How do the techniques compare in terms of the time taken for optimization and training?”, it was concluded that the SVM takes considerably less time to optimize and train than the ANN and the RF, and the ANN takes considerably less time to optimize and train than the RF.

In response to the second research sub-question posed which asked “How do the techniques compare in terms of the final classification accuracy on unseen images once they have been optimized and trained?”, it was concluded that while all three techniques are very accurate and comparable in terms of classification accuracy, all three achieving exceptionally high overall accuracies of over 80%, the ANN can be considered more accurate than the SVM and RF, and the SVM can be considered more accurate than the RF.

In response to the third and final research sub-question posed as “How do the techniques compare in terms of the time taken to achieve a classification result on a single input once they have been optimized and trained?”, it was concluded that the ANN and RF both take an exceptionally small amount of time to classify a single image, and are both many orders of magnitude faster than the SVM, but the RF takes considerably less time to classify a single image than the ANN.

Therefore, and finally, in response to the main research question which was phrased as "How do Support Vector Machines, Artificial Neural Networks and Random Forests compare in the context of SASL hand shape recognition?", it was concluded that the ANN is more accurate and consistent than the SVM and RF, the SVM is considerably quicker to optimize and train than the ANN and RF given a trained and optimized classification model, and the RF is considerably faster than the ANN and SVM when it comes to classifying a single input image given a trained and optimized classification model.

Overall, it was concluded that the ANN is the most suitable classifier, given it is the most accurate and consistent classifier, and has an exceptionally high classification speed that is comparable to that of the RF, and both of these factors justify the optimization and training time which is more than the SVM but less than the RF.

These finding have made a significant contribution to the field of hand shape recognition, and to the research of the SASL project. They have clearly demonstrated that the basis of this research—carrying out a comparison of machine learning techniques in the context of a specific classification problem—is crucial. This is because, while an arbitrary machine learning technique such as SVMs can serve as a good classifier, as was used originally by Li [36], this research has shown that it may not be, and in the context of SASL hand shape recognition, is not the optimal choice.

This research has also significantly contributed to the SASL group, first, by producing an improved SASL hand shape classifier. More importantly, it has produced a methodology that can be used in future to determine optimal machine learning techniques for other classification problems such as facial expression, hand location, hand orientation and hand motion recognition.

6.1 Future Work

The ANN technique has proven to be the better technique amongst the three chosen machine learning techniques in the context of SASL hand shape recognition. In future, the ANN-based system can, therefore, be incorporated into the SASL gesture recognition system to achieve an improved accuracy, and exceptional computational speed.

This research provides a basis and methodology for comparing machine learning techniques in a specific context. In future, this approach can be used to determine optimal classifiers for each of the SASL systems that recognize various SASL parameters.

Finally, while this research has determined that ANNs are better than SVMs and RFs, the investigation may be extended to other machine learning techniques such as Naive Bayes classifiers and Hidden Markov Models, which may prove to be better than ANNs for SASL hand shape recognition.

6.2 Concluding Remarks

The researcher has found the research and experiments conducted throughout this course to have been an excellent growth experience. It is hoped that this research can serve as a basis and methodology for the selection of optimal machine learning techniques for other sign language parameters by the SASL group, and for classification problems in general.

Appendix A

Additional Optimization Results

Number of Hidden Neurons m	**Accuracy (%)**
2	18.33
3	29.53
4	36.36
5	44.50
6	50.40
7	63.73
8	67.63
9	68.43
10	63.26
11	70.73
12	71.96
13	73.93
14	71.40
15	69.30
16	74.70
17	73.37
18	74.30
19	72.37
20	74.73
21	73.60
22	74.13
23	74.70
24	73.66
25	74.03
26	71.67
27	74.80
28	74.96
29	73.40
30	75.03
31	75.73
32	74.76
33	74.46
34	74.73
35	74.13
36	75.23
37	75.00
38	73.70
39	75.40
40	76.23
41	74.93
42	75.97
43	73.57
44	74.13
45	75.33
46	76.70
47	76.26
48	76.53
49	74.43
50	76.77

(cont. right)

TABLE A.1: The hidden neurons and their corresponding cross-validation accuracies

No. of Trees	**Depth $D_{\mathbf{min}}$**									
B	2	4	6	8	10	12	14	16	18	20
5	19.50	29.43	36.30	40.33	42.07	43.10	49.20	43.87	46.40	45.47
10	20.30	35.20	45.73	48.40	52.57	53.63	57.27	55.50	54.03	53.53
15	25.00	40.80	48.03	53.60	59.57	59.53	59.80	62.33	59.73	60.33
20	30.67	41.36	53.30	56.60	61.60	65.30	64.07	63.67	63.73	65.20
25	30.23	41.93	52.93	59.90	62.83	67.03	65.90	65.50	64.93	67.30
30	31.30	44.83	54.30	60.10	65.30	68.20	66.90	65.67	65.23	68.20
35	33.20	45.10	54.33	61.67	64.97	68.80	67.13	65.63	65.23	68.37
40	33.57	46.20	54.67	64.67	65.90	69.57	67.13	65.63	65.23	68.37
45	34.73	47.07	56.20	65.03	66.90	69.97	67.13	65.63	65.23	68.37
50	35.97	47.77	56.40	66.40	66.80	70.03	67.13	65.63	65.20	68.37
55	38.93	47.73	56.53	66.60	66.93	70.03	67.13	65.63	65.23	68.37
60	37.90	48.93	58.27	67.33	66.90	70.03	67.13	65.63	65.23	68.37
65	38.23	49.83	59.27	67.23	67.27	70.03	67.13	65.63	65.23	68.37
70	38.23	49.83	59.27	67.23	67.27	70.03	67.13	65.63	65.23	68.37
75	39.07	49.73	59.50	67.57	67.27	70.03	67.13	65.63	65.23	68.37
80	38.83	51.43	61.13	67.83	67.63	70.03	67.13	65.63	65.23	68.37
85	39.70	50.93	60.67	67.83	67.63	70.03	67.13	65.63	65.23	68.37
90	40.13	50.77	60.50	67.80	67.63	70.03	67.13	65.63	65.23	68.37

TABLE A.2: The cross-validation accuracies for Random Forests

Appendix B

Additional Test Results

Subject	Hand Shape									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
7	50	46	50	43	50	50	49	50	50	14
8	50	49	50	50	49	50	50	50	13	2
9	50	50	1	17	1	49	43	50	5	32
10	46	48	44	40	49	49	50	49	50	19
11	50	48	50	27	47	30	50	50	50	50
12	50	22	50	50	50	48	50	50	50	50
Total	296	263	245	227	246	276	292	299	218	167

Table B.1: Classification accuracy per subject of the Support Vector Machine.

Subject	Hand Shape									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
7	50	45	50	41	50	49	48	48	50	27
8	50	49	50	49	48	50	50	49	14	48
9	50	50	1	21	17	48	43	49	34	43
10	44	50	39	24	31	49	48	49	50	19
11	50	44	50	33	47	30	50	50	50	50
22	45	6	50	50	50	49	50	50	50	50
Total	289	244	240	218	243	275	289	295	248	237

Table B.2: Classification accuracy per subject of the Artificial Neural Network.

Subject	**Hand Shape**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
7	49	20	50	48	48	49	50	47	50	20
8	44	47	50	50	47	50	50	50	30	16
9	50	48	3	31	5	47	43	46	5	43
10	38	17	25	41	35	50	43	48	50	16
11	49	44	50	25	45	31	50	50	50	50
12	50	2	50	50	50	48	50	50	50	47
Total	280	178	228	245	230	275	286	291	235	192

Table B.3: Classification accuracy per subject of the Random Forest.

Actual	**Predicted**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**296**	0	0	3	0	0	0	0	1	0
2	0	**263**	35	0	0	2	0	0	0	0
3	0	4	**245**	0	0	0	6	2	0	43
4	66	0	0	**227**	7	0	0	0	0	0
5	46	1	0	3	**246**	0	0	4	0	0
6	0	24	0	0	0	**276**	0	0	0	0
7	1	0	2	0	2	0	**292**	1	2	0
8	0	0	1	0	0	0	0	**299**	0	0
9	0	0	0	41	0	0	35	6	**218**	0
10	130	0	0	0	0	0	0	3	0	**167**

Table B.4: Confusion matrix for the recognition accuracy of the Support Vector Machine.

Actual	**Predicted**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**289**	0	0	1	0	0	3	1	1	5
2	0	**244**	49	0	0	7	0	0	0	0
3	0	4	**240**	1	0	0	1	5	1	48
4	13	4	0	**218**	53	0	9	0	1	2
5	19	0	0	17	**243**	0	1	10	0	10
6	0	25	0	0	0	**275**	0	0	0	0
7	5	0	2	1	2	0	**289**	0	0	1
8	0	1	0	1	2	0	0	**295**	1	0
9	0	0	0	10	0	0	36	6	**248**	0
10	23	2	0	6	0	3	0	6	23	**237**

Table B.5: Confusion matrix for the recognition accuracy of the Artificial Neural Network.

Actual	Predicted									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	**280**	1	2	0	4	0	6	1	4	2
2	0	**178**	108	0	0	9	0	5	0	0
3	7	15	**228**	0	0	0	0	1	0	49
4	31	0	0	**245**	9	0	8	0	0	7
5	6	2	0	1	**230**	0	1	55	0	5
6	0	24	1	0	0	**275**	0	0	0	0
7	1	1	2	0	1	0	**286**	2	2	5
8	0	1	2	2	0	4	0	**291**	0	0
9	0	14	0	12	0	14	23	2	**235**	0
10	76	0	7	0	0	8	3	5	9	**192**

Table B.6: Confusion matrix for the recognition accuracy of the Random Forest.

Bibliography

[1] S. Abu-Nimeh, D. Nappa, X. Wang, and S. Nair, "A comparison of machine learning techniques for phishing detection," in *Proceedings of the Anti-phishing Working Groups 2nd Annual eCrime Researchers Summit*. ACM, 2007, pp. 60–69.

[2] I. Achmed, "Upper body pose recognition and estimation towards the translation of South African Sign Language," Master's thesis, University of the Western Cape, Computer Science, 2010.

[3] I. Achmed, I. M. Venter, and P. Eisert, "A framework for independent hand tracking in unconstrained environments," in *Proceedings of the Southern Africa Telecommunication Networks and Applications Conference 2012*, George, South Africa, 2012.

[4] M. Ali and D. Clausi, "Using the Canny edge detector for feature extraction and enhancement of remote sensing images," in *Geoscience and Remote Sensing Symposium, 2001. IGARSS'01*, vol. 5, 2001, pp. 2298–2300.

[5] K. Asmal and W. James, "Education and democracy in South Africa today," *Daedalus*, pp. 185–204, 2001.

[6] H. Avilés-Arriaga, L. Sucar-Succar, C. Mendoza-Durán, and L. Pineda-Cortés, "A comparison of dynamic naive Bayesian classifiers and Hidden Markov Models for gesture recognition," *Journal of Applied Research and Technology*, vol. 9, no. 1, pp. 81–100, 2011.

[7] G. Bebis and M. Georgiopoulos, "Feed-forward neural networks," *Potentials, IEEE*, vol. 13, no. 4, pp. 27–31, 1994.

[8] G. Borgefors, "An improved version of the chamfer matching algorithm," in *Proceedings of the 7th International Conference on Pattern Recognition*, vol. 2, Montreal, Canada, 1984, pp. 1175–1177.

[9] T. Borovicka, M. Jirina Jr, P. Kordik, and M. Jirina, "Selecting representative data sets," *Advances in Data Mining Knowledge Discovery and Applications. Intech*, 2012.

[10] G. Bradski, “Real time face and object tracking as a component of perceptual user interface,” in *Proceedings of the Fourth IEEE Workshop on Applications of Computer Vision*, 1998, pp. 214–219.

[11] L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[12] D. Brown, “Upper body pose recognition and estimation towards the translation of South African Sign Language,” Master’s thesis, University of the Western Cape, Computer Science, 2013.

[13] J. Canny, “A computational approach to edge detection,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, no. 6, pp. 679–698, 1986.

[14] C. Cortes and V. Vapnik, “Support-vector networks,” *Machine learning*, vol. 20, no. 3, pp. 273–297, 1995.

[15] A. Criminisi and J. Shotton, *Decision forests for computer vision and medical image analysis.* Springer, 2013.

[16] M. Dewar, “Characterization and evaluation of aged 20Cr32Ni1Nb stainless steels,” Master’s thesis, Department of Chemical and Materials Engineering, University of Alberta, Canada, 2013.

[17] A. Elgammal, C. Muang, and D. Hu, *Skin detection—A short tutorial.* Springer, 2009.

[18] M. M. Fleck, D. A. Forsyth, and C. Bregler, “Finding naked people,” in *Computer VisionECCV’96.* Springer, 1996, pp. 593–602.

[19] H. Freeman, “Computer processing of line-drawing images,” *ACM Computing Surveys*, vol. 6, no. 1, pp. 57–97, 1974.

[20] I. Frieslaar, “Robust south african sign language gesture recognition using hand motion and shape,” Master’s thesis, University of the Western Cape, Computer Science, 2014.

[21] M. Ghaziasgar, “The use of mobile phones as service-delivery devices in a sign language machine translation system,” Master’s thesis, University of the Western Cape, Computer Science, 2010.

[22] M. Glaser and W. D. Tucker, “Telecommunications bridging between deaf and hearing users in South Africa,” in *Proceedings of the Conference and Workshop on Assistive Technologies for People with Vision and Hearing Impairments*, Granada, Spain, 2004.

[23] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning.* Springer, 2009.

[24] R. Hecht-Nielsen, "Theory of the backpropagation neural network," in *International Joint Conference on Neural Networks, IJCNNA'89*, 1989, pp. 593–605.

[25] C. Hsu, C. Chang, and C. Lin, "A practical guide to support vector classification," National Taiwan University, Tech. Rep., 2003.

[26] C. Hsu and C. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Transactions on Neural Networks*, vol. 13, no. 2, pp. 415–425, 2002.

[27] R. Hsu, M. Abdel-Mottaleb, and A. Jain, "Face detection in color images," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2002, pp. 696–706.

[28] M. Jones and J.M.Rehg, "Statistical color models with application to skin detection," Cambridge Research Laboratory, Tech. Rep., 1996.

[29] M. Kadous, "Machine recognition of Auslan signs using Powergloves:towards large-lexicon recognition of sign language," Master's thesis, University of New South Wales, Computer Science and Engineering, 1995.

[30] B. Karlik and A. V. Olgac, "Performance analysis of various activation functions in generalized MLP architectures of neural networks," *International Journal of Artificial Intelligence and Expert Systems*, vol. 1, no. 4, pp. 111–122, 2011.

[31] E. Keating and G. Mirus, "American sign language in virtual space: Interactions between deaf users of computer-mediated video communication and the impact of technology on language practices," *Language in Society*, vol. 32, no. 5, pp. 693–714, 2003.

[32] N. B. Kiyaga and D. F. Moores, "Deafness in sub-Saharan Africa," *American Annals of the Deaf*, vol. 148, no. 1, pp. 18–24, 2003.

[33] V. S. Kulkarni and S. Lokhande, "Appearance based recognition of American Sign Language using gesture segmentation," *International Journal on Computer Science and Engineering*, vol. 2, no. 03, pp. 560–565, 2010.

[34] A. Kuznetsova, L. Leal-Taixé, and B. Rosenhahns, "Real-time sign language recognition using a depth camera," in *IEEE International Conference on Computer Vision Workshops*, 2013, pp. 83–90.

[35] Y. Lee, S. Min, H. Yang, and K. Jung, "Motion sensitive glove-based Korean finger-spelling tutor," in *Proceedings of the 2007 International Conference on Convergence Information Technology*, ser. ICCIT '07. Washington, DC, USA: IEEE Computer Society, 2007, pp. 1674–1677.

[36] P. Li, "Hand shape estimation for South African Sign Language," Master's thesis, University of the Western Cape, Computer Science, 2010.

[37] R. Maini and H. Aggarwal, "Study and comparison of various image edge detection techniques," *International Journal of Image Processing (IJIP)*, vol. 3, no. 1, pp. 1–11, 2009.

[38] S. Marcel, "Hand posture and gesture datasets," [Online] Available at http://www.idiap.ch/resource/gestures.

[39] A. Maruch, "Talking with the hearing-impaired," January 2010, [Online] Available at http://www.deafsa.co.za/index-2.html.

[40] W. S. McCulloch and W. Pitts, "A logical calculus of the ideas immanent in nervous activity," *The Bulletin of Mathematical Biophysics*, vol. 5, no. 4, pp. 115–133, 1943.

[41] K. Mehrotra, C. K. Mohan, and S. Ranka, *Elements of Artificial Neural Networks*. MIT Press, 1997.

[42] M. Minsky and S. Papert, *Perceptrons*. MIT Press, 1969.

[43] M. Minsky and S. Papert, *Perceptrons: An introduction to computational geometry, Expanded Editon*. MIT Press, 1988.

[44] D. Mushfieldt, "Robust facial expression recognition in the presence of rotation and partial occlusion," Master's thesis, University of the Western Cape, Computer Science, 2014.

[45] W. Nel, "An integrated sign language recognition system," Master's thesis, University of the Western Cape, Computer Science, 2014.

[46] T.-N. Nguyen, H.-H. Huynh, and J. Meunier, "Static hand gesture recognition using artificial neural network," *Journal of Image and Graphics*, 2013.

[47] I. Nitze, U. Schulthess, and H. Asche, "Comparison of machine learning algorithms random forest, artificial neural network and support vector machine to maximum likelihood for supervised crop type classification," in *Proceedings of the 4th Geobia, Rio de Janeiro—Brazil*, 2012.

[48] OpenCV documentation, "Introduction to support vector machines," 2014. [Online]. Available: http://docs.opencv.org/doc/tutorials/ml/introduction_to_svm/introduction_to_svm.html

[49] V. Patil and S. Shimpi, "Handwritten English character recognition using neural network," *Elixir Computi. Sci. Eng.*, vol. 41, pp. 5587–5591, 2011.

[50] J. C. Platt, N. Cristianini, and J. Shawe-Taylor, "Large margin dags for multiclass classification." in *Advances in Neural Information Processing Systems 12*, 1999, pp. 547–553.

[51] N. Pugeault, "The ASL finger spelling dataset," [Online] Available at http://personal.ee.surrey.ac.uk/Personal/N.Pugeault/index.php?section=FingerSpellingDataset.

[52] A. Réda and B. Aoued, "Artificial neural network-based face recognition," in *First International Symposium on Control, Communications and Signal Processing, 2004.*, 2004, pp. 439–442.

[53] K. O. Rodríguez and G. C. Chávez, "Finger spelling recognition from RGB-D information using kernel descriptor," in *Proceedings of the 2013 XXVI Conference on Graphics, Patterns and Images*, ser. SIBGRAPI '13. Washington, DC, USA: IEEE Computer Society, 2013, pp. 1–7.

[54] F. Rosenblatt, "The perceptron: a probabilistic model for information storage and organization in the brain." *Psychological Review*, vol. 65, no. 6, pp. 386–408, 1958.

[55] H. Rowley, "Frontal face images," [Online] Available at http://vasc.ri.cmuedu/ idb/ html/ face/frontal_images/.

[56] M. Sharifi, M. Fathy, and M. Tayefeh Mahmoudi, "A classified and comparative study of edge detection algorithms," in *Proceedings of the International Conference on Information Technology: Coding and Computing, 2002*, 2002, pp. 117–120.

[57] C. Stauffer and W. Grimson, "Adaptive background mixture models for real-time tracking," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2, pp. 246–252, Jun. 1999.

[58] C. Stobbart and E. Alant, "Home-based literacy experiences of severely to profoundly deaf preschoolers and their hearing parents," *Journal of Developmental and Physical Disabilities*, vol. 20, no. 2, pp. 139–153, 2008.

[59] W. C. Stokoe, "Sign language structure: An outline of the visual communication systems of the american deaf. studies in linguistics: Occasional papers," Buffalo: Dept. of Anthropology and Linguistics, University of Buffalo, Tech. Rep. 8, 1960.

[60] Y. Tabata and T. Kuroda, "Finger spelling recognition using distinctive features of hand shape," in *International Confernece on Disability, Virtual Reality and Associated Technologies with Art Abilitation*, no. 7, 2008, pp. 287–292.

[61] Y. Tabata, T. Kuroda, and K. Okamoto, "Development of a glove-type input device with the minimum number of sensors for Japanese finger spelling," in *Proceedings of*

International Conference on Disability, Virtual Reality and Associated Technologies, no. 9, 2012, pp. 305–310.

[62] P. Trigueiros, F. Ribeiro, and L. P. Reis, "A comparison of machine learning algorithms applied to hand gesture recognition," in *Proceedings of the 7th Iberian Conference on Information Systems and Technologies (CISTI)*. IEEE, 2012, pp. 1–6.

[63] P. E. Utgoff, "Incremental induction of decision trees," *Machine learning*, vol. 4, no. 2, pp. 161–186, 1989.

[64] D. van Wyk, "Virtual human modelling and animation for sign language visualisation," Master's thesis, University of the Western Cape, Computer Science, 2008.

[65] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *Proceedings of the IEEE Computer Society International Conference on Computer Vision and Pattern Recognition*, 2001, pp. 511–518.

[66] P. Viola and M. Jones, "Robust real-time object detection," *International Journal of Computer Vision*, vol. 57, no. 2, pp. 137–154, 2004.

[67] L. Wang, Y. Hang, S. Luo, X. Luo, and X. Jiang, "Deblurring Gaussian-blur images: A preprocessing for rail head surface defect detection," in *Proceedings of IEEE International Conference on Service Operations, Logistics, and Informatics (SOLI)*, 2011, pp. 451–456.

[68] Y. Wang, H. Ai, B. Wu, and C. Huang, "Real time facial expression recognition with adaboost," in *Proceedings of the 17th International Conference on Pattern Recognition (ICPR)*, vol. 3. IEEE, 2004, pp. 926–929.

[69] J. Whitehill, "Automatic real-time facial expression recognition for signed language translation," Master's thesis, University of the Western Cape, Computer Science, 2006.

[70] J. Whitehill and C. W. Omlin, "Haar features for FACS AU recognition," in *7th International Conference on Automatic Face and Gesture Recognition, 2006*. IEEE, 2006, pp. 97–101.