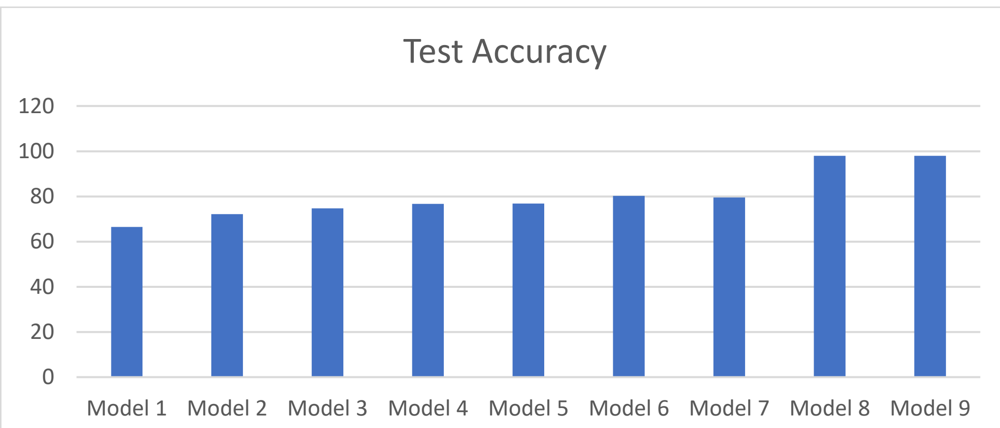
	Training Sample	Validation Sample	Test Sample	Epoch	Optimizer	Regularization	Dropout	Augmentation	Pretrained	Test Accuracy	Test Loss
Model 1	1000	500	1000	30	rmsprop	No	No	No	No	66.5	62.3
Model 2	1000	500	1000	10	rmsprop	Yes	0.5	Yes	No	72.15	57.3
Model 3	1500	500	500	10	rmsprop	No	No	No	No	74.7	51.9
Model 4	1500	500	500	15	rmsprop	Yes	0.5	Yes	No	76.7	48.4
Model 5	2000	500	1000	10	rmsprop	No	No	No	No	76.8	49.3
Model 6	2500	500	500	15	adam	No	No	No	No	80.2	43.18
Model 7	2000	500	1000	15	rmsprop	Yes	0.5	Yes	No	79.5	48.3
Model 8	1000	500	1000	15	rmsprop	Yes	No	No	No	97.9	69.3
Model 9	2000	500	1000	10	adam	Yes	0.5	Yes	Yes	97.9	68.47

When we increased our sample size, we found that our model improved in terms of test accuracy, even without using techniques like data augmentation or dropout for regularization. For instance, when we had a training sample of 2000, our fifth model achieved a test accuracy of 76.8%, which was much higher than our initial model (model 1). When we incorporated dropout and data augmentation, the models performed even better. With 2000 training samples, the RMSprop optimizer, and a 0.5 dropout rate, our seventh model reached a test accuracy of 79.5% (model 7). Changing the optimizer to Adam resulted in an accuracy of 80.2% (model 6).



The best test accuracy was obtained using a pre-trained model with the Adam optimizer, a dropout rate of 0.5, and data augmentation, reaching 97.9% test accuracy. Notably, even with the same sample size, the pre-trained model outperformed models trained from scratch, with or without regularization. Additionally, it is worth mentioning that increasing the sample size for the pre-trained model didn't have a significant effect on performance of the pre-trained model. This suggests that sample size plays a more critical role when building models from scratch compared to when using pre-trained models.