# CONCLUSION

In this paper, we pose the problem of fraudulent insurance claim identification as a feature generation and classification process. We formulate the problem over a minimal, definitive claim data consisting of procedure and diagnosis codes, because accessing richer datasets are often prohibited by law and present inconsistencies among different software systems. We introduce clinical concepts over procedure and diagnosis codes as a new representation learning approach. We assume that every claim is a representation of latent or obvious Mixtures of Clinical Concepts which in turn are mixtures of diagnosis and procedure codes. We extend the MCC model using Long-Short Term Memory network (MCC + LSTM) and Robust Principal Component Analysis (MCC + RPCA) to filter the significant

concepts from claims and classify them as fraudulent or non fraudulent. Our results demonstrate an improvement scope to find fraudulent healthcare claims with minimal information. Both MCC and MCC + RPCA exhibit consistent behavior for varying concept sizes and replacement probabilities in the negative claim generation process. MCC + LSTM reaches an accuracy, precision, and recall scores of 59%, 61%, and 50%, respectively on the inpatient dataset. Besides, it presents 78%, 83%, and 72% accuracy, precision, and recall scores, respectively on the outpatient dataset. We notice similarity between the results of MCC and MCC + RPCA, as both use an SVM classifier. We believe that the proposed problem formulation, representation learning and solution will initiate new research on fraudulent insurance claim detection using minimal, but definitive data.