CONCEALED FIREARM DETECTION ON VIDEO SURVEILLANCE USING SKELETAL TRACKING AND MACHINE LEARNING TECHNIQUES

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Definition of Key Terms

- **Carrying a Concealed Firearm** is the practice of carrying weapons such as a handgun in public in a concealed manner either on one's body or in close proximity to one's body.
- **Concealed Firearm Detection** are the various techniques used to detect and identify concealed firearms on individuals (Khajone & Shandilya, 2012).
- **Human Skeletal Tracking** is the processing of depth image data to establish the positions of various skeleton joints on a human form(Webb & Ashley, 2012).
- **Computer Vision** is the process of **modelling** and **replicating** human vision using computers (Zhang, et al., 2009).
- **Machine Learning** is a field of computer science that uses statistical techniques to give **computers** the **ability to "learn", without being explicitly programmed** (Zhang, et al., 2009).

Background

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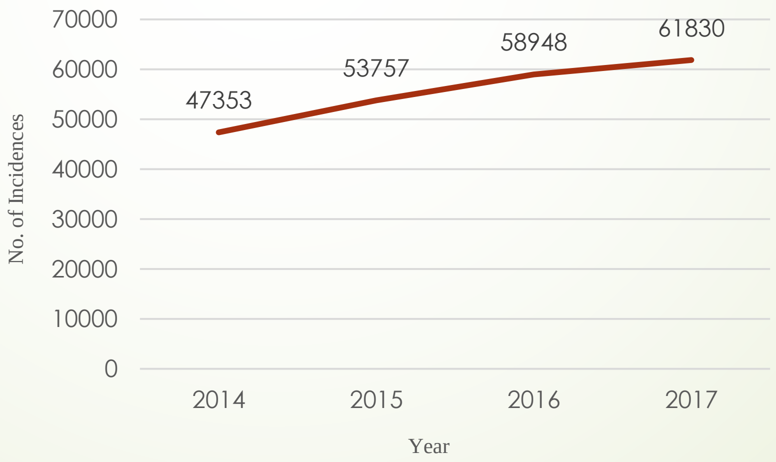
- Incidences involving illegal firearms have been on a **steady rise** worldwide (**Gun Violence Archive, 2018**). In Kenya, the national police service annual crime report indicates that **over a third** of all criminal offences in major towns in the country involved the use of a firearm (**National Police Service, 2017**). Most of these illegal firearms are carried in a **concealed manner** to the location where they will be used to commit a crime (**Meehan & Strange, 2015;Porter, 2010**).



Incidences Involving Firearms in the US

Background: Concealed Firearm Detection Techniques

- It is against this background that the detection of weapons **concealed underneath a person's cloths** is very much important to the improvement of public security(**Bandyopadhyay, Datta, & Roy, 2012**).
- Various **security measures** have been employed to **counter this threat.**
  - **Visual Inspection** and **Pat Downs** (**Gopinath, Krishna, & Srilatha, 2014**).
  - Using **Metal Detectors-** (**Nelson, Kantor, & Nakamura, 2015**).
  - Behavioral Analysis using trained CCTV operators in CCTV mediated Surveillance (**Darker, Blechko, & Gale, 2009; Gunes et al., 2015**).
  - **Automated Video Surveillance** using **Image Sensor Technologies** (**Pate et al., 2016; Salmon, 2008**).

Background: Limitations of Presently used techniques

- A common challenge with Pat downs and the use of metal detectors is that they are Invasive and the close proximity with which they are used (Nelson, Kantor, & Nakamura, 2015; Ploch, Dĕkan, & Zýka, 2015).
- Behavioral analysis suffers from inefficiencies due to **human weaknesses**. (Arroyo et al., 2015; SenthilKimar & Narmatha, 2016).
- A common challenge with automated Video Surveillance techniques is that they rely on the active scanning of **stationary** and **co-operative** persons in a **controlled environment** as illustrated below.

Statement of the problem

- Current attempts to have intelligent video surveillance to detect firearms concealed underneath a person's clothing have been found to be **impractical** since persons being screened have to be **stationary** and **cooperative** (Hegde, Shivaprasad , & Neh, 2015; Sirakov, 2015)
- A desirable solution would be one that is able to detect persons carrying concealed firearms without them being **stationary** or **aware** (Darker, Gale, & Blechko, 2008; Grega, Matiola 'nski, Guzik, & Leszczuk, 2016).

Purpose and Scope of the Study

- The purpose of this study is to develop a machine learning-based model that can correctly identify a person carrying a handgun concealed on their hip by tracking their skeletal motion on Video.
- This will enable the detection of concealed firearms while a person is in motion and unaware that they are being screened.
- Why detection of Firearms concealed on the hip?
  - Arkchiefs, (2017); Meehan & Strange, (2015); Porter, (2010) indicate that most illegal firearms are carried in a concealed manner and tucked on the hip without a holster to facilitate easier access. This is specifically, on the right side of the waist, back and crotch areas.

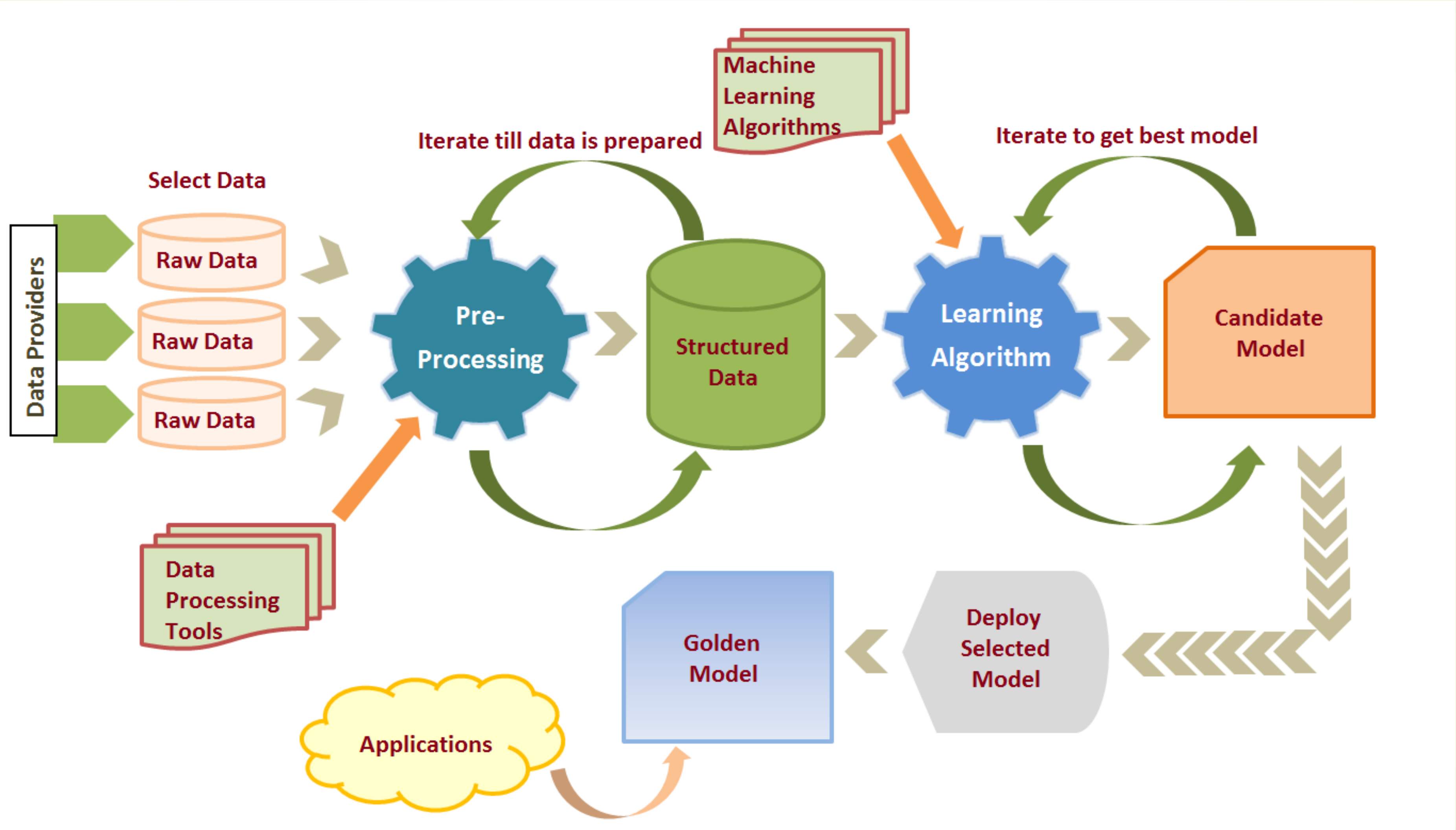
Why Human Motion Tracking?

- **Darker, Blechko, and Gale, (2009) found that motion(gait)is often and accurately used body language by CCTV operators in CCTV mediated Surveillance to identify persons carrying concealed firearms.**
- **In addition, its very difficult for a person to hide/alter their gait as compared to other body language such as facial expressions and eye movements (Gunes, Shan, Chen, & Tian, 2015; Kleinsmith & Bianchi-Berthouze, 2013).**

Assumptions of the Study

- Dataset used was recorded in a lab environment. The study assumes that participant motion was not affected by their knowledge that they were being recorded.
- The study assumes that the developed dataset is an accurate representation of the problem and hence the results are generalizable.

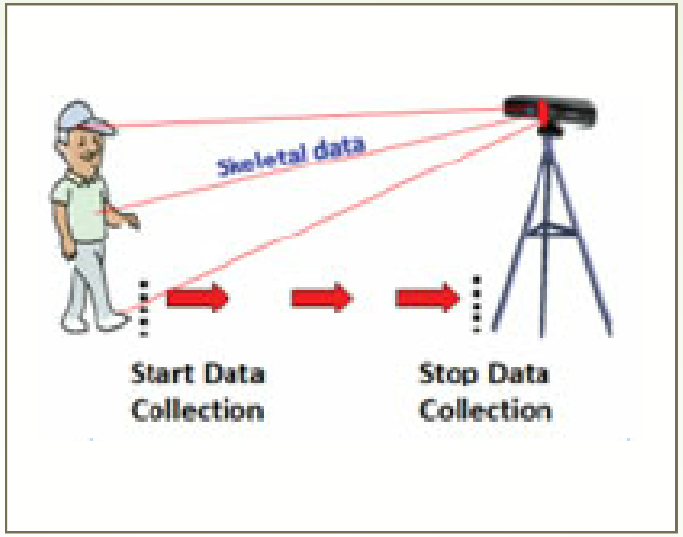
Methodology Procedure

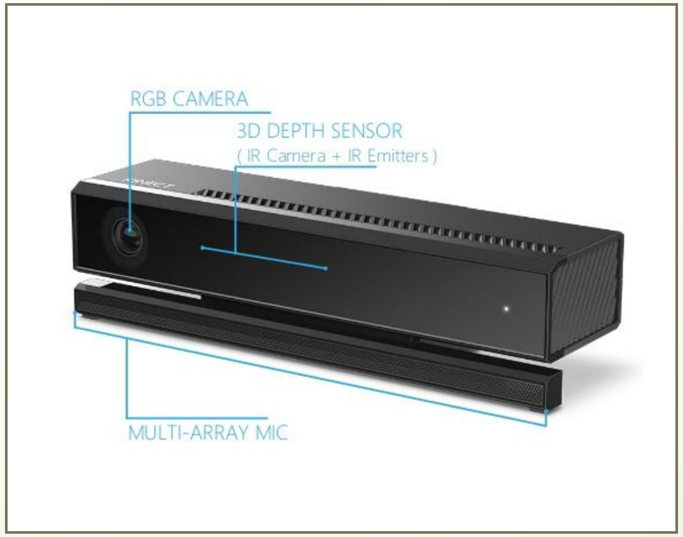


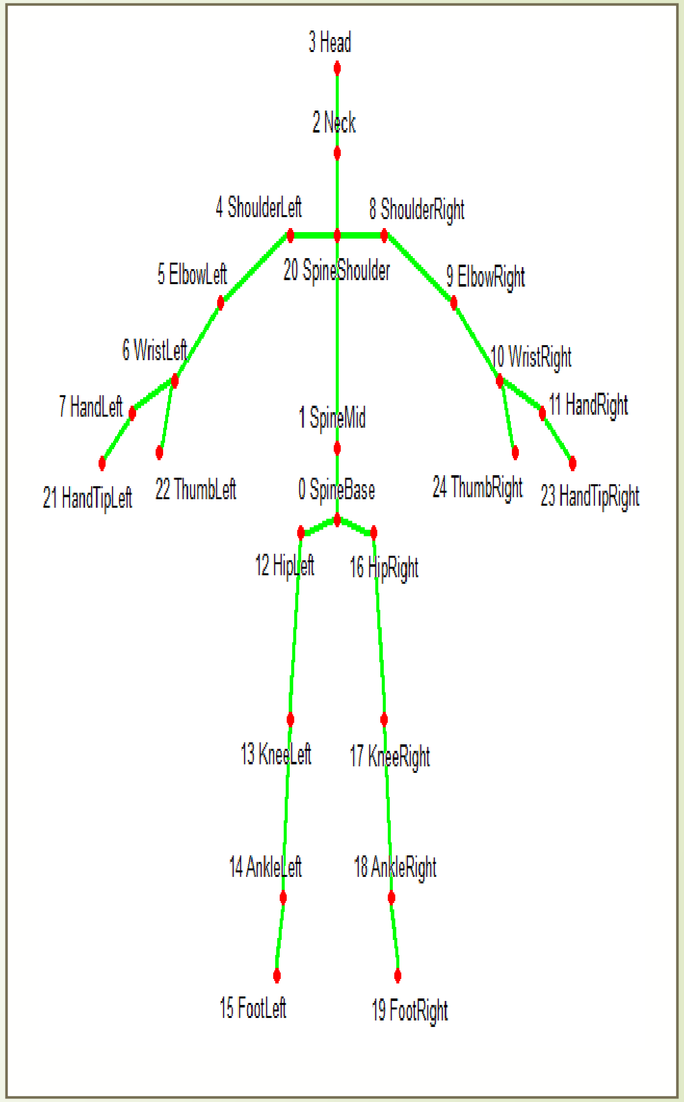
(Sarkar,Bali & Sharma, 2017)

Data Acquisition

- Repeated Measures Research Design
- 26 Participants (19 M and 7 F)
- All participants wore a trouser and a jacket
- Ceska Firearm tucked on the right hip.
- Data acquired is in form of distance vector from the sensor







Data Pre-processing

1 Data Normalization

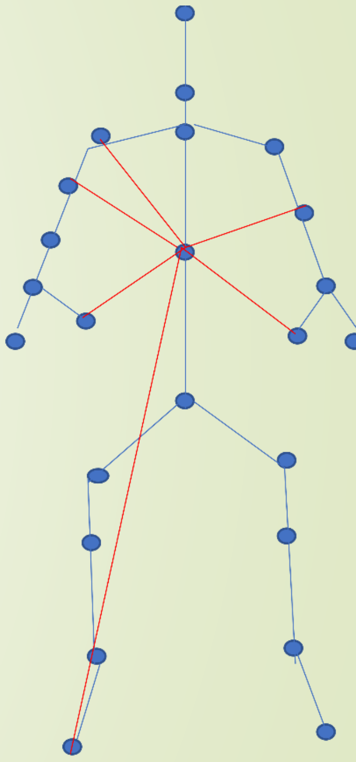
- Acquired data was dependent on sensor and participants dimensions
- Normalization using pair wise relative position-spatial displacement (Translation and scaling)
- The resultant data is a set of distance vectors which connect each joint to the spine mid joint.
- Tool used: MATLAB

2 Feature Vector Engineering

- All vectors from the *N* recorded frames were combined into a row feature vector
- All 25 joints were included in the feature vector (FV) resulting to 75-3D distance features.
- In total the FV had 4525 instances with 3434 for male and 1091 for female.

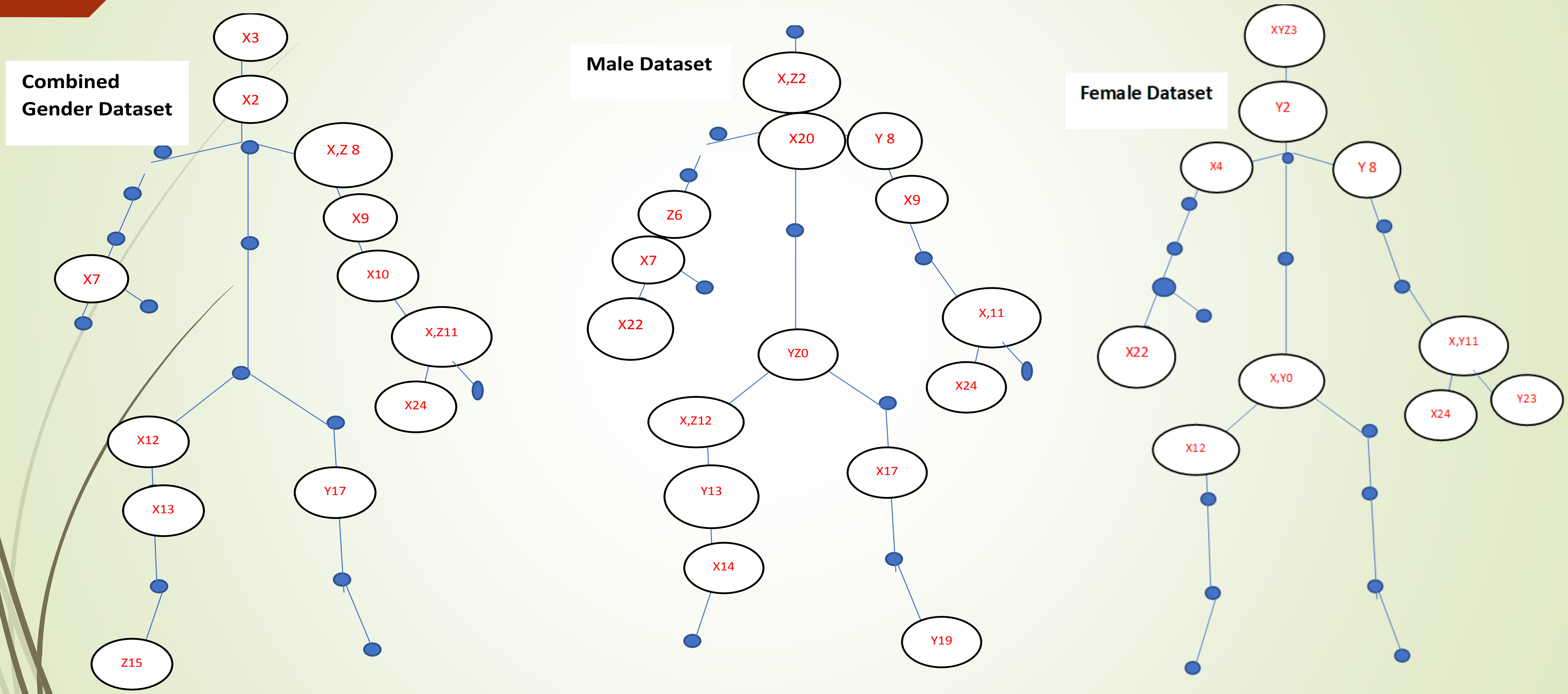
3 Feature Selection

- Feature vector had high dimensionality and could lead to model over-fitting
- Feature Selection using wrapper method with C4.5 decision tree classifier and best fit search method
- Tool used: WEKA datamining workbench



Distance vector

Feature Selection Experiment Results



Discussion of Feature Selection Results

- Selected Features are different in all datasets. Signifying that concealed firearm carrying affects the motion of male and females' differently.
- In female's, feature representing the legs were not selected. This signifies that leg movement is not affected by concealed firearm carrying.
- The coordinate axis that is predominant in the selected features is the X-axis. This signifies that concealed firearm carrying has a greater impact on motion along this axis.

Machine Learning Experiment Results-Combined Data Set

Algorithm	Accuracy	Recall/ Sensitivity-TPR	Specificity/ TNR	F-Measure	Cohen-Kappa Statistic
Zero-R Baseline	0.511	0.511	1.00	0.511	0.00
Naïve Bayes	0.637	0.637	0.649	0.637	0.274
kNN/IBK	0.962	0.962	0.962	0.962	0.925
C4.5 Decision Tree	0.814	0.814	0.807	0.813	0.628
Random Forest	0.933	0.933	0.927	0.933	0.867
Support Vector Machine (SVM)	0.665	0.665	0.671	0.665	0.340

Machine Learning Experiment Results-Male Data Set

Algorithm	Accuracy	Recall/ Sensitivity	Specificity	F-Measure	Cohen-Kappa Statistic
Zero-R Baseline	0.516	0.516	0.516	0.000	0.000
Naïve Bayes	0.541	0.541	0.533	0.473	0.620
kNN/IBK	0.978	0978	0.979	0.978	0.956
C4.5 Decision Tree	0.824	0.824	0.827	0.824	0.648
Random Forest	0.946	0.946	0.945	0.946	0.891
Support Vector Machine (SVM)	0.616	0.616	0.611	0.613	0.228

Machine Learning Experiment Results-Female Data Set

Algorithm	Accuracy	Recall/ Sensitivity	Specificity	F-Measure	Cohen-Kappa Statistic
Zero-R Baseline	0.532	0.532	0.532	0.000	0.000
Naïve Bayes	0.622	0.622	0.688	0.619	0.253
kNN/IBK	0.986	0.986	0.988	0.986	0.972
C4.5 Decision Tree	0.875	0.875	0.878	0.875	0.749
Random Forest	0.967	0.967	0.967	0.967	0.934
Support Vector Machine (SVM)	0.706	0.706	0.687	0.700	0.401

Discussion of Machine Learning Results

- In all data sets, the ML algorithms performed exceedingly better than the baseline algorithm (Zero R).
- KNN algorithm outperformed all other algorithms with 96% in all metrics for all datasets followed by random forest. The specificity and sensitivity was high specificity is an indication of sufficient true positives (classification of armed) while a high specificity is an indication of sufficient true negatives (unarmed) and minimal false alarms.
- General Classification of females' was the best followed by male and finally the combined dataset. However, the performance difference was minimal (0.024)
- Overall, Naïve Bayes and Support vector machine algorithms performed way below other algorithms. This could be investigated in future research.

Conclusions ,Recommendations and Future Works

- The machine learning results point to the viability of motion analysis using depth data for concealed firearm detection in both male and female. This is consistent with the findings by (Darker, Blechko, and Gale, 2009) which employed a qualitative approach.
- This approach for concealed firearm detection can be integrated into existing video surveillance networks to mitigate the identified challenges with existing techniques.
- The K-nearest neighbor algorithm demonstrates superior performance and can be used for the integration.
- Future research
  - Study firearms concealed at the back and front hip
  - Explore the use of Deep Learning


Thank you