Detection and Profiling of Synthetic Opioids

by

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A thesis submitted for the

Degree of Doctor of Philosophy (Science)

University of Technology Sydney

Certificate of authorship and originality

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Abbreviations

%RSD Relative Standard Deviation

2-BEB (2-bromoethyl)benzene

2-CEB (2-chloroethyl)benzene

4-ANPP 4-anilino-N-phenethylpiperidine

4-FBF 4-fluorobutyryl fentanyl

ABS Australian Bureau of Statistics

ACIC Australian Criminal Intelligence Commission

ACMD Advisory Council on the Misuse of Drugs

ACN Acetonitrile

AFP Australian Federal Police

AIDIP Australian Illicit Drug Intelligence Program

AIHW Australian Institute of Health and Welfare

ANN Artificial Neural Network

AORC Association of Official Racing Chemists

ARFL Australian Racing Forensic Laboratory

ATS Amphetamine-type Stimulants

CAS Chemical Attribution Signature

CE Collision Energy

CE-DAD Capillary Electrophoresis – Diode Array Detector

CID Collision-induced Dissociation

CRM Certified Reference Material

CSV Comma-separated Value

DALY Disability-adjusted Life Years

DBE Double Bond Equivalents

DCM Dichloromethane

DDA Data-dependent Acquisition

DEA Drug Enforcement Administration

DIA Data-independent Acquisition

DIPEA Diisopropylethylamine

EIC Extracted Ion Chromatogram

EMCDDA European Monitoring Centre for Drugs and Drug Addiction

ESI Electrospray Ionisation

ESI+ Positive Electrospray Ionisation Mode

EWA Early Warning Advisory

FbF Find by Formula

FbI Find by Ion

FTIR Fourier Transform Infra-red Spectroscopy

FWHM Full Width at Half Maximum

GC-MS Gas Chromatography – Mass Spectrometry

GPR Gaussian Process Regression

HR High Resolution

HRMS High-resolution Mass Spectrometry

Hy Hydrophilic Factor

ICP-MS Inductively Coupled Plasma – Mass Spectrometry

IS Internal Standard

KMD Kendrick Mass Defect

Liquid Chromatography – Evaporative Light Scattering Detector

LC-MS Liquid Chromatography – Mass Spectrometry

LC-QTOF-MS Liquid Chromatography – Quadrupole Time of Flight – Mass Spectrometry

LD₅₀ Median Lethal Dose

LR Low Resolution

m/z Mass-to-charge Ratio

MALDI Matrix-assisted Laser Desorption/Ionisation

MCC Matthew's Correlation Coefficient

MCR Multicomponent reaction

MDA 3,4-methylenedioxyamphetamine

MDF Mass Defect Filtering

MDMA 3,4-methylenedioxymethamphetamine

MFE Molecular Feature Extraction

MPP Mass Profiler Professional

MRM Multiple Reaction Monitoring

MS/MS Tandem Mass Spectrometry

MSC Molecular Structure Correlator

MS^E Elevated Mass Spectrometry

MSE Mean Square Error

NDSHS National Drug Safety Household Survey

NIST National Institute of Standards and Technology

NLF Neutral Loss Filtering

NMI National Measurement Institute

NMR Nuclear Magnetic Resonance Spectroscopy

NPF Non-pharmaceutical Fentanyl

NPP N-phenethyl-4-piperidone

NPS New Psychoactive Substances

NSO Novel Synthetic Opioid

ONDCP Office of National Drug Control Policy

PCA Principal Component Analysis

PCDL Personal Compound Database and Library

PIS Product Ion Searching

PLS-DA Partial Least Squares – Discriminant Analysis

PMMA Para-methoxymethylamphetamine

QqQ Triple Quadrupole

RFE Recursive Feature Extraction

RMSE Root Mean Square Error

RRT Relative Retention Time

RT Retention Time

S/N Signal-to-noise Ratio

SD Standard Deviation

SPE Solid Phase Extraction

STRL Special Testing and Research Laboratory

SVM Support Vector Machine

SWATH Sequential Windowed Acquisition of All Theoretical Fragment Ion Mass Spectra

SWGDRUG Scientific Working Group for the Analysis of Seized Drugs

TBAB Tetra-N-butylammonium bromide

TIC Total Ion Chromatogram

UHPLC-MS Ultra High-performance Liquid Chromatography – Mass Spectrometry

UNODC United Nations Office on Drugs and Crime

VBA Visual Basic for Applications

Publications and Conference Proceedings

Refereed Journal Publications

- 1. **Klingberg, J.**, et al., *Collision-Induced Dissociation Studies of Synthetic Opioids for Non-targeted Analysis.* Front. Chem., 2019. **7**(331).
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Abstract

Synthetic opioids are a drug class of particular concern due to their incredibly high potency and the large public health threat that they pose. These compounds have also seen significant modification, highlighting the importance of developing techniques that can detect them without relying on databases or certified reference materials. This work provides a comprehensive investigation into the detection and profiling of synthetic opioids from the perspective of both drug screening in biological matrices and analysis of seized drug samples.

Collision-induced dissociation studies were conducted on a range of different synthetic opioid standards and common product ions belonging to each opioid subclass were identified for use in non-targeted screening strategies. Product ion searching, Kendrick Mass Defect analysis and recursive feature extraction approaches were evaluated for data analysis. Product ion searching and Kendrick mass defect analysis proved effective, with estimated screening cut-offs proposed of 0.05 ng/mL and 0.1 ng/mL, respectively. Recursive feature extraction was found to have a high sensitivity for the detection of spiked compounds, however unbiased extraction of all compounds within a sample presented issues with relevance for screening.

Machine learning approaches were investigated for the identification of unknown compounds. A Naïve Bayes classification model was trained, exploiting the common fragmentation pathways identified, to predict the opioid subclass of a sample with 89.5% accuracy. Additionally, a Gaussian Process Regression model was optimised to predict the experimental relative retention time of a compound based on its molecular features. Relative retention times were predicted for 79.7% of the samples within ±0.1 of their experimental value. By using these models as complementary approaches putative identities of unknown compounds can be proposed with greater confidence before confirmation using certified reference materials.

A preliminary study was also conducted into the synthetic route profiling of acetyl fentanyl. Several common impurities were identified, as well as a number of impurities that were unique to a specific method. These impurities can provide an analyst with an indication of the method used in the synthesis of a seized sample. Furthermore, a statistical approach was taken, with the creation of principal component analysis plots and classification models. The PCA plots showed distinct separation between samples made with different methods and the trained classification models

displayed high accuracy. These results should be reviewed in context, however, as small sample sizes were used in this preliminary study.