AN INDEX MAPPING-BASED DEEP TRANSFER LEARNING APPROACH FOR VIOLENT CRIME PREDICTION

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LIST OF ABBREVIATIONS

| Acronyms | Full Meaning |
|----------|---|
| ANN | Artificial Neural Network |
| API | Application Programming Interface |
| ASP | Active-X Server Pages |
| ASM | Attributes Selection Measures |
| BP | Back Propagation |
| CC | Control Server |
| CNN | Convolutional Neural Network |
| CPTED | Crime Preventions Through Environmental Design |
| CSS | Cascading Style Sheet |
| DB | Database |
| DBSCAN | Density Based Spatial Clustering Application with Noise |
| DEEPTRA | Deep Transfer learning |
| DL | Decision Learning |
| DNN | Deep Neural Network |
| DT | Decision Tree |
| DTL-NN | Deep Transfer Learning Neural Network |
| EE | Enterprise Edition |
| EJB | Enterprise Java Beans |
| FBI | Federal Bureau of Investigation |
| FCT | Federal Capital Territory |
| GPS | Global Positioning System |
| GUI | Graphics User Interface |
| HTML | Hyper Text Markup Language |
| HTTP | Hyper Text Transfer Protocols |
| IDE | Integrated Development Environment |
| ІоТ | Internet of Things |
| JDBC | Java Database Connectivity |
| | |

| JS | JavaScript |
|--------|--|
| JSON | JavaScript Object Notation |
| JVM | Java Virtual Machine |
| KDE | Kernel Density Estimation |
| KNN | K- Nearest Neighbor |
| LAMP | Linus Apache MySQL and PHP |
| ME | Mobile Edition |
| ML | Machine Learning |
| MLLib | Machine Learning Libraries |
| MLP | Machine Learning Programs |
| NLP | Natural Language Processing |
| NoSQL | No Structured Query Language |
| OCR | Optical Character Recognition |
| PCA | Principal Components Analysis |
| PHP | Hyper Text Preprocessor |
| RDBMS | Relational Database Management System |
| SE | Standard Edition |
| SOCP | Second Order Cone Programming |
| SQL | Structured Query Language |
| SUS | System Usability Scale |
| SVM | Support Vector Machine |
| TD-IDF | Term Document and Inverse Document Frequency |
| UCPS | Ubiquitous Crime Prevention System |
| VVT | Voice to Text |
| WAMP | Windows Apache MySQL and PHP |
| XAMPP | Cross Platform Apache MySQL PHP and Perl |
| XML | extra Markup Language |

AN INDEX MAPPING-BASED DEEP TRANSFER LEARNING APPROACH FOR VIOLENT CRIME PREDICTION

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A THESIS SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY (Ph.D) IN COMPUTER SCIENCE IN THE DEPARTMENT OF COMPUTER AND INFORMATION SCIENCES, COLLEGE OF SCIENCE AND TECHNOLOGY, COVENANT UNIVERSITY, OTA.

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ABSTRACT

Crime has been with us from time immemorial and impacts negatively on the quality of life of citenzery and the general health of a nation. Different approaches have been used in the previous studies for violent crime prediction to aid predictive policing, making conventional policing more efficient and proactive. The violent crime rate in Nigeria has been on the continual increase. There are dearths of state-of-the-art measures like the predictive policing approach for violent crime prediction in Nigeria. The existing controlling and preventive measures for tracking and controlling violent crime are not sufficient. The violent crime predictive models in the previous studies do not have sufficient features to predict violent crime types and time-slot of violent crime occurrences. More so, violent crime occurrence prediction is nearly impossible when there is insufficient dataset. Therefore the aim of this study is to develop an improved predictive model for violent crime prediction using an index mapping-based deep transfer learning approach with a view to increasing the predictive accuracy of violent crime prediction in Nigeria. The sources of data for this study are from historical violent crime records of Nigerian Police, and online reported violent crime data. As a prelude to generating training data, cleaning of data and relevant feature selection of violent crime dataset were performed. Consequently the predictive model developed during the empirical study was trained on IBM Watson Machine Learning studio. The model consists of four layers: data collection, features extraction, spatio-temporal violent crime prediction premised on index mapping-based deep transfer learning, and violent crime hot spot visualizer layer. The evaluation experiment was conducted through benchmarking with the existing approaches using accuracy, semantic precision, and recall as well as F-measure metrics with the use of confusion matrix. The violent crime prediction model evolved in this study delivers a predictive accuracy of 92.53% across the six violent crime dataset used. This result showed that an index mapping-based deep transfer learning model developed outperformed other Machine Learning models used in the previous studies. In addition, the proof-of-concept web-based application for reporting and alerting violent crime developed was also evaluated through a system usability scale survey with a result of 85.28%, which represent usable system with good usability rating score. The study therefore serves to benefit the citizens of Nigeria by alerting them of violent crime hotspot areas in the country, and also would enable police authority develop violent crime prevention strategies that could mitigate spate of criminal activities in the country.

Keywords: Convolutional Neural Network, Deep Learning, Index mapping, Recurrent Neural Network, Transfer Learning, Hot spot, Violent Crime Prediction.

ACCEPTANCE

This is to attest that this thesis is accepted in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy (Ph.D) in Computer Science in the Department of Computer and Information Sciences, College of Science and Technology, Covenant University, Ota, Nigeria

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I attest that this thesis has not been presented either wholly or partially for the award of any degree elsewhere. All the sources of the data and scholarly information used in the thesis were duly acknowledged.

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Signature and Date

CERTIFICATION

We certify that the thesis titled **"An Index-mapping based Deep Transfer Learning Approach for Violent Crime Prediction"** is an original research work carried out by **FALADE, ADESOLA MURITALA (13PCG00484)**, in the Department of Computer and Information Sciences, College of Science and Technology, Covenant University, Ogun State, Nigeria under the supervision of Prof. Ambrose A. Azeta and Dr. Aderonke A. Oni. We have examined and found the work acceptable as part of the requirements for the award of a degree of Doctor of Philosophy (Ph.D) in Computer Science.

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DEDICATION

This research study is dedicated to the glory of Almighty God, the Alpha and the Omega, the light of the World who granted me the grace to start and finish the Ph.D programme successfully. Mighty God, I thank you.

Also, to the loving memory of my beloved parent who took care of me from childhood. May their gentle souls rest in the bosom of the Lord.

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