Predicting the Future How Deep Learning is Revolutionizing Stem Cell Therapy Outcomes

Abstract

Regenerating therapy using stem cells has proved to be a future area of regenerative medicine which can cure people of degenerative disorders, damage to organs and chronic diseases. Nevertheless, it is a significant challenge to know the therapeutic outcomes because of the occurrence of variability in patients, protracted cell differentiation pathways, and spontaneously unfixed immune completion. The recent explosion in deep learning has made possible new ways to model such complexities using high-dimensional biomedical data, such as imaging, genomics and clinical records. [3]
In this paper, the author will venture into the use of the latest deep learning architectures, including convolutional neural networks, recurrent neural networks, and transformer-based models to predict the success rates of stem cell treatment, optimize treatment plans, and predict risk. [6]
These models can be used to extract patterns not perceptible by humans through analysis of the corpus of data, by synthesizing the multimodal datasets. We overview existing approaches, point to the examples of the use of AI that have achieved a meaningful change in the predictive accuracy, and review the difficulties that interpretability of complex models, sparsity of data, and the problem of clinical validation among. We have briefly analyzed how deep learning will revolutionize the progress of stem cell treatments, in linking the gap between the laboratory and the clinic thus leading to safer, efficacious, and patient-specific stem cell treatments.

Journal
Journal of Science, Technology and Engineering Research.

Volume-II, Issue-III-2024

Pages: 1-11

Keywords

Deep Learning, Stem Cell Therapy, Predictive Analytics, Regenerative Medicine, Artificial Intelligence, Biomedical Imaging

1. Introduction

The field of stem cell therapy is one of the beneficiaries of regenerative medicine as it can be used to repair, replace or regenerate flawed tissues and organs. Stem cell intervention is promising in terms of treatment of neurodegenerative diseases and cardiovascular diseases and in the regeneration of organs. [2] Nevertheless, even though stem cell biology has advanced tremendously, it is not a simple task to anticipate therapeutic outcomes. Individual patients of the

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

same regimen of treatment often respond differently as regards to factors of genetic heterogeneity, immune matches etc. and even purely because of the nature of the stem cell populations. This volatility makes it very difficult to make clinical decisions and hinders the process of translating what has been found in the laboratory into safe, effective therapy. [4]

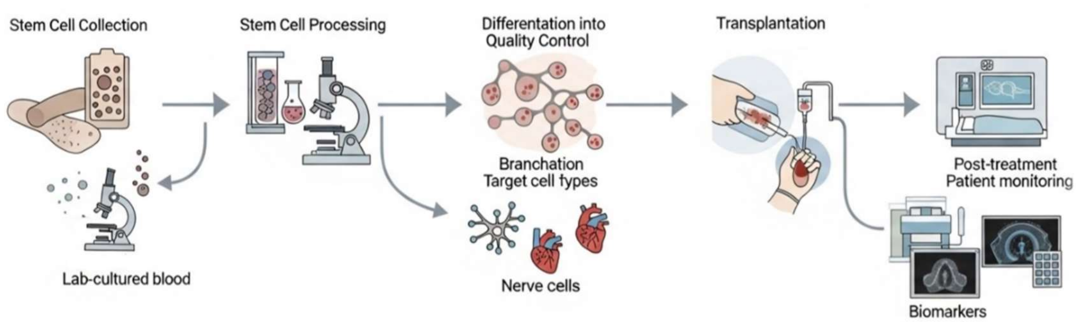

Figure-1

Artificial intelligence (AI) and deep learning, especially, has become an effective instrument of biomedical research in the last several years. Deep learning can model highly complex, nonlinear relationships between large data sets that at times may not be discernible with standard statistical techniques or even to analysts. These models can combine heterogeneous data sources, such as high-resolution cell imaging, multi-omics sequencing data, and rich patient medical history, to predict treatment outcomes with growing precision, in the situation of stem cell therapy. [5]

Integration of deep learning and stem cell therapy has the potential to contribute to rapid transition to precision regenerative medicine. Predictive models may help clinicians choose the best types of stem cells, approximate the success rate of stem cell differentiation, identify subtle indexes of the immune system rejection, and reduce the chance of negative effects. Furthermore, explicable AI is enabling the discovery of the biological determinants influencing predictions and, hence, clinical credibility and understanding.

This paper discusses the present existing state of deep learning in the prediction of stem cell therapy outcomes. We analyze merit worthy literature, the change in methodology, case studies that have proven clinical potential, and the complications while pointing out the way forward in making AI-driven prediction come to the regenerative medicine workflow.

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

2. Literature Review

2.1 Background of the Stem cell Therapy

There is the potential of using stem cell therapy which is an outcome of specialized cell self-renewal and differentiation potential of stem cells that may have the potential to cure degenerative, traumatic and congenital diseases. There are other types of stem cells used in both clinical and preclinical application: [2]

Embryonic Stem Cells (ESCs): The pluripotent cells that have the potential to differentiate into almost all cell types, commonly referred to as the ethical and tumorigenic issues.

Induced Pluripotent Stem cells (iPSCs): Somatic cells changed to pluripotent state and that provide species-specific match in patients, with fewer ethical restrictions.

Mesenchymal Stem Cells (MSCs): Multipotent stromal cell characterized with high immunomodulatory effects, which usually come in the form of bone marrow, adipose tissue cells or umbilical cord blood cells.

Clinical results of this therapeutic potential are inconsistent because of differences in donors, situational disease, and inability to predictively know how to differentiate this process in vivo.

2.2 Obstacles to Prediction of Therapeutic Outcome

Stem cell therapy has been shown to lie under dependence of many biological and clinical factors:

Cellular Heterogeneity: Within a single batch, there can be different levels of stem cells with respect to potency, differentiation pathway and survival.

The Variability of Immune Response: Immune responses of patients can take away transplanted cells causing failure of treatment. Complexity of the Disease: Backdrops of pathologies, gene susceptibilities and comorbid conditions impact the activity of the medications.

Monitoring Weaknesses: Current clinical monitoring is mostly dependent on imaging and following up of biomarkers which might not detect the early signs of failure of the therapy. [4]

Conventional statistical models are inadequate in approximating the high-dimensional, nonlinear dynamics of these factors and thus more sophisticated methods of analysis are required.

2.3 Deep Learning in Biomedical Research

Deep learning refers to a subclass of machine learning in which multi-layer neural networks can be trained to fit complex patterns on large datasets. Deep learning has already proven successful in healthcare in**:** Medical Imaging Analysis: CNNs are best in the field of radiology, pathology, and histology image classification because it reaches professional accuracy.

Transcriptomic and Genomic Data Processing: Recurrent Neural Networks (RNNs) and Transformers discover gene-disease interactions and reveal the regulative mechanism.

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

Drug Discovery and Cell Behavior Prediction: Generative models such as Variational Auto encoders (VAEs) or Generative Adversarial Networks (GANs) are generative models used to model the structure of molecules and predict the biological outcome. [6]

Such capabilities render deep learning as an appropriate methodology in predicting the outcome of stem cell therapy treatments, especially in the context of combining multimodal data.

2.4 Deep Learning in Stem Cell research applications

The recent researches addressed the AI-based strategies of regenerative medicine:

Morphological Quality Assessment: CNN-based models are able to distinguish the quality of stem cell colonies on the basis of microscopy images, contributing to picking the most operable cultures to transplant.

Differentiation Prediction: Forecasts of the probability of stem cells developing into desired lineages have been predicted with time-lapse imaging with LSTM networks. [3]

Safety Profiling: By training a deep learning model on datasets of preclinical studies, the measurement of tumorigenic potential can be performed prior to the event.

Patient-Specific Outcome Forecasting: Multimodal AI solutions consisting of ommics, imaging, and clinical history have provided potential to predict the post-therapy functional recovery rates.

2.5 Research Gaps

Regardless of such encouraging advances, there is a number of gaps. Unavailability of big, high quality, annotated datasets with regard to stem cell therapies. The lack of understandability of deep learning predictions, which become an issue in gaining regulatory approval. Lack of clinical trials to introduce decision-making with AI into the treatment plans. The necessity of having a standardized measure of evaluation of predictive models between studies. It will be important to fill these gaps so that deep learning-based predictions can be translated into everyday clinical practice.

3. Methodological Approaches in Prediction

Creation of high predictive models of stem cell therapy outcomes starts with obtaining high-quality and varied data sets that show both biological as well as clinical variables. Image analysis, particularly by microscopy and histology imaging, is important because it gives high-quality pictures of colony morphology, cell confluence and differentiation stages. A complementary molecular view is provided by genomic, transcriptomic and proteomic profiling, which identify trends in gene expression and epigenetic marks, and signaling cascades of proteins that can affect the fate of stem cells. The personalized predictions are initially provided in the context of clinical records and demographic records (for example, the age of the patient and disease stage, as well as past treatment, immune profiles). Moreover, the longitudinal monitoring data, including biomarker values, functional recovery scale, and follow-up imaging, record the dynamics of changes triggered by a therapy after an appropriate time range. [5]

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

The use of the different types of deep learning architecture varies according to the data used and the goal of prediction. Convolutional Neural Networks (CNNs) are popular in performing image-based analysis, including the classification of the quality of stem cell colonies or assessment of the slight morphological variations associated with aberrant differentiation. Recounting and ordered data, the Recurrent Neural Networks (RNNs) and a modified one, Long Short-Term Memory (LSTM) networks, are especially efficient. Self-attention-based transformer models are also used in an attempt to merge multimodal data, such as genomic sequences and written clinical notes. [7] In specific conditions in rare diseases, generative models (Generative Adversarial Network) (GANs) and Variational Auto encoders (VAEs) can be used to simulate cell growth patterns or supplement training data. [8] The hybrid architectures which blend CNN, RNN, and attention modules are becoming potent to capture both the spatial and temporal dependencies in complicated biomedical data.

There are various factors that should be considered in training and validation of models. Preprocessing preliminaries which include normalization, augmentation of images, dimensionality reduction of omics data sets, repair of missing clinical values are needed to make the models robust. Transfer learning is often applied to learn the previously developed pre trained models on big biomedical data and minimize the need to develop a model on a huge, stem cell-specific labeled data. Statistically valid performance estimates by cross-validation methods such as k-fold and stratified methods are ensured. The architecture is then finely optimized by hyper parameter optimization techniques (e.g., grid search, Bayesian optimization, or evolutionary algorithms) to optimally predict.

The assessment of the performance of the models in the context needs to be on multidimensional basis. Accuracy, precision, recall, F1-score, the area under the ROC curve (ROC-AUC) are typical metrics used in classification tasks. Depending on the measures, any prediction, according to the regression theory, can assume a basis on measures like mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R^2). In survival analysis, the concordance indices (C-index) and Kaplan Meier Survival curves are able to give information on time to event forecasts. Notably, such issues as sensitivity to the early warning of therapy failure, roles of the different number needed to treat (NNT) and false-negative rates are required to indicate the clinical utility of models in healthcare environments.

As an example of these methodological solutions, the example of quality assessment of stem cell colonies with the help of microscope-based CNN models could be cited. Such models, when trained on annotated image datasets may be able to read nuanced morphological clues related to the potential of differentiation, or early onset cell pathology to allow clinicians to choose the best appearing cultures to transplant. [1] Likewise, multimodal architectures that combine genomic information with EHRs over time have proven to predict patient-specific recovery outcomes, which provides a route to more personal and effective regenerative therapeutics.

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

4. Findings from Literature

The impact of deep learning in the research field of stem cell therapy has been found to produce impressive results with regards to various areas of application. Investigations dealing with the image-based quality assessment have shown over and over again that the convolutional neural networks have a greater chance of detecting high potential stem cells colonies in comparison to the traditional methods of analyzing the images. As a case in point, CNN models trained on high-resolution microscopy images have demonstrated classification accuracies of well over 90%, and can be used to automatically select colonies most likely to differentiate successfully. [3] This type of automation decreases the use of manual expert judgement hence minimizing the chances of human error and maximize the process throughput in laboratory processes.

In predicting differentiation potential, time lapse imaging together with sequential modelling strategy, including LSTM networks has shown efficacy in specific temporal variability in cell morphology. Through these models, one can predict the various trajectories of differentiation a few days before making it possible to give researchers preliminary information on how the stem cells would be developing. Transformer-based models have also demonstrated promise in using imaging data in combination with a multi-omics profile, with predictions not only being highly predictive, but also indicating biologically important features leading to treatment effects. [6]

One more sphere where the application of deep learning has been observed is safety assessment. Genomic and phenotypic data have been used to train models that can predict tumorigenic risk with great sensitivity on preclinical datasets. [10] Such systems, in preventing the use of one of the potentially unsafe cell line candidates in transplantation procedures, could minimize one of the most serious safety issues in regenerative medicine. There is also potential in predictive models implemented using patient-specific clinical data to estimate the functional recovery rates after treatment; thus enabling clinicians to better customize interventions to the specific patients.

In spite of these achievements, there are also some limitations, which are mentioned in the literature. The importation of small dataset sizes may be a running problem in many studies as it reduces the model generalizability and also may lead to overfitting. In addition, accuracy scores can be high in experimental trials and not many studies have proved their models in prospective clinical trials, thus, it remains an open question regarding their practicality in real life. Clinical decision-makers will also not be ready to integrate AI tools into therapeutic procedures without clear explanations of the factors that affect their predictions since interpretability of deep learning models has always been an issue.

Overall, the existing studies indicate that the deep learning can be well-positioned to change the manner in which outcomes of stem cell therapy are predicted. It has been demonstrated that the technology can solve the problem of its predictive accuracy, automate previously laborious processes, and assimilate mixed biomedical data. Nevertheless, to move such breakthroughs into the regular clinical practice, the problems of the quality of a dataset, regulatory approachability, and the transparency of the model will have to be addressed.

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

5. Discussion

The literature survey reveals that deep learning can be of high potential in improving the accuracy of the predictive outcome of stem cell therapy. The ability of the neural networks to represent complicated nonlinear patterns of multimodal biomedical data aligns them as disruptive technologies in regenerative medicine. As an example, convolutional neural networks have been shown to be able to identify subtle morphological features on images in image-based assessments that humans cannot, which can be used to select viable stem cell colonies earlier and more reliably than humans due to being computerized. Likewise, the combination of omics data and clinical records into multimodal platforms has opened the possibility of enhanced patient-specific prognostication and furthering the dream of personalized regenerative medicine. [2]

Nevertheless, the journey to the clinical application still cannot be seen as immediate and free of impediments. Among the most urgent problems, two aspects should be mentioned: data scarcity and fragmentation. Institution-specific datasets used in stem cell research are usually small and therefore it restricts the generalizability of models. Although, transfer learning and data augmentation may help overcome this shortcoming at least partially, development of big, standardized and publicly available datasets will be necessary in order to generate models that can be deployed in clinical practice on a large-scale basis. Joint data-sharing programs among research institutions, hospitals, and biobanks can offer a potential way forward, but it also should be handled with care to ensure privacy and regulatory-wise delivery of patients.

The other pitfall that majorly affects deep learning is the interpretability of predictions. Opaque outputs in the form of not easily interpretable black boxes will be unlikely to earn the standards of regulatory agencies or physician trust in a clinical setting. Techniques like saliency mapping and feature attribution methods, known as explainable AI (XAI) techniques, may be used to make the decisions that models make more easily understood by clinicians, providing them with a clearer foundation upon which to pass judgment on an AI decision. The interpretability is especially preferable in applications where the miscalculation of risk may have serious consequences like the tumorigenic risk determination.

Ethical and regulatory aspects are relevant in assessing the possibility to incorporate AI in the workflows used in stem cell therapy as well. Problems of algorithmic bias, lack of parity of access to AI-powered diagnostics, and consent to the use of personal data need to be considered beforehand. Regulatory frameworks will have to become flexible to the current AI systems that do provide decision support but also change and improve as time goes by through continuous learning.

In the future, deep learning will probably be further established in stem cell therapy in predictive analytics becoming real-time monitoring and adaptive treatment planning. Given the ability to couple wearable biosensors, advanced imaging modalities, and AI-based predictions, clinicians could monitor the responses to therapies on a per-patient basis and potentially adjust and update interventions in the process. In addition, federated learning, which trains models on many institutions without exposing raw data, may serve the purposes of alleviating data scarcity and privacy issues at the same time. [11]

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

Finally, when combined with the stem cell treatment, deep learning can change regenerative medicine to become more accurate, predictable, and personal. Achieving this vision will need a long term coordinated effort between AI researchers, stem cell biologists, clinicians, and ethicists as well as medical regulatory agencies. These efforts potentially can merge into the second beginning when the treatment plans are not only scientifically but also ethically correct, transparent, and individually oriented toward the patient.

6. Challenges & Future Directions

Although deep learning shows transformational potentials when it comes to predicting the outcome of stem cell therapy, there are a number of issues that need to be resolved before these mechanisms can be incorporated into clinical practice. Among the most important obstacles, there is the low availability of big, high-quality, and standardized datasets. A large percentage of existing studies use small institution level data that constrains generalizability and risk overfitting the developed models. The fact that the data formats, imaging protocols, and the structure of patient's records may be heterogeneous is another compounding problem at research institutions. Large scale, multi-institutional, and harmonized dataset creation will be imperative towards creating models that can achieve reliability across a variety of clinical settings. [7]

The other difficulty consists in making deep learning models understandable. Although the predictive accuracy of the models is high, clinicians and regulators express opposition to a black box model because potential clinicians need clear reasoning behind a recommendation of therapeutics. Introducing the methods of explainable AI (XAI) into predictive pipelines might help to enhance their transparency and inspire trust among medical experts. The methods would not only indicate the features that matter in the predictions but potentially yield some new findings in biomedicine on the mechanisms of stem cell biology and stem cell therapy approaches.

There are further complexities of ethical and regulatory issues. The effects of the training of AI on biased datasets can be carried to the field without intending to discriminate against a certain group of patients who may be underexposed. It will be critical to provide algorithmic fairness by collecting moderated data and detecting bias. Moreover, genomic and clinical data are sensitive data, and therefore the privacy preservation has to be done strongly, including but not limited to encryption, safe data-sharing practices, and adherence to security policies, including the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA).

Technologically, further studies ought to look into incorporating multimodal data streams that assemble imaging, omics, clinical records, and real-time biosensors information into collective predictive interpolations. The introduction of such aspects as federated learning may allow receiving privately trained models developed in several institutions, thus making the information more diverse and better privacy-related. [9] The development of self-supervised learning might also assist in breaking the need to use labor-intensive practices of data labeling so that models can acquire bigger amounts of unlabeled biomedical data.

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

Deep learning may be applied in the long term to enable dynamic prediction, which would enable dynamic and adaptive treatment. Entailing constant variability in predictions due to a flow of patient data, AI systems would allow making dynamic changes in treatment, enhancing its effectiveness and minimizing the chances of poor outcomes. Finally, the terrain needs long-term multi-disciplinary partnership between AI developers, scientists in stem-cell research, clinicians, bioethicist, and regulatory bodies. These coordinated activities represent the only way to ultimately deliver the potential of AI-driven stem cell therapy in scale and give birth to a new era in precision regenerative medicine.

Conclusion

Stem cell therapy is the most promising of regenerative medicine that provides unequal opportunities to treat, and even reverse the effects of degenerative diseases, traumatic injuries, and congenital defects. However, its potential is still limited by the random nature of the results of the therapy. The prediction of the efficiency and safety of the treatment cannot be predicted very accurately due to patient-specific variation, the variety of the effect of treatment as easily due to the natural heterogeneity of the biological effect on the host and recipient cells by stem cells and finally the complex interaction between stem cells and the host environment. Conventional statistical methods, although important, are also not sufficient to describe the nonlinear high-dimensional dependencies that characterize such biological processes.

Deep learning has become a promising complement to traditional biomedical analytics, promising the capacity to consume large and heterogeneous streams of data, whether on cellular images or genomic sequences or comprehensive clinical histories, as well as capable of discerning faint and multi-dimensional structures that might inform therapeutic success or failure. The mentioned literature used in the current paper shows that convolutional neural networks have outperformed traditional techniques of analyzing images in the process of determining the quality of stem cells, how recurrent and transformer-based networks have facilitated predictive analysis by using time-series and multimodal data, and how a generative approach can be used to expand the data analysis research capabilities in simulation and data augmentation. Collectively, the aforementioned developments show that artificial intelligence cannot be construed as a mere ancillary instrument but as a possible accelerator to a paradigm change towards predictive and personalized regenerative medicine.

There are, however, other challenges to the translation of deep learning-driven predictions in making the leap between research and clinical practice. There should be solutions to such issues as data scarcity, absence of standard protocols, the clarity of data models, and ethical aspects of patient data privacy in order to receive a safe, fair transition. Overcoming such limitations will necessitate multilateral, cross-disciplinary partnership, in that AI developers will be joined by stem cell biologists, clinicians, ethicists, and policymakers. Such teamwork will not only create increased reliability and trust of predictive models but also will create regulatory beaches that meet the unique needs of data-driven, adaptable medical technologies.

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

Moving forward, the direction of stem cell therapy can be outlined as the smooth introduction into all phases of treatment, including the selection of patients, the processing of stem cells, monitoring after the treatment, and the planning of the adaptation interventions. It is possible that deep learning combined with the modern capabilities in real-time bio sensing, high- throughput omics and cloud-supported approaches to clinical decision support may enable the therapeutic approach to be refined on an ongoing basis using real-time data on live patients. Similarly, in this vision, treatment plans would be dynamic and, depending on the patient, evolve to the unique physiological pathway of that patient, optimized both in terms of efficacy with the lowest risks.

Deep learning provides a revolutionizing way towards resolving uncertain results that is only one of the most challenging obstacles of stem cell therapy. With the help of the predictive capabilities of AI, regenerative medicine will place a step on the way to achieving its potential, namely, to provide more than innovative treatment, but accurate, personalized, and evidence-based care. Whether the route to the translation of laboratory innovation to clinical practice will prove easy or hard is an open question, but the value of that path, quantifiable in better patient outcomes and extended access to life-changing treatments, is tremendous.

References

1. Samuel, A. J. (2023). Enhancing financial fraud detection with AI and cloud-based big data analytics: Security implications. SSRN. http://dx.doi.org/10.2139/ssrn.5273292
2. Fatunmbi, T. O. (2022). Leveraging robotics, artificial intelligence, and machine learning for enhanced disease diagnosis and treatment: Advanced integrative approaches for precision medicine. World Journal of Advanced Engineering Technology and Sciences, 6(2), 121–135. https://doi.org/10.30574/wjaets.2022.6.2.0057
3. You, Y., Lai, X., Pan, Y., Zheng, H., Vera, J., Liu, S., Deng, S., & Zhang, L. (2022). Artificial intelligence in cancer target identification and drug discovery. Signal Transduction and Targeted Therapy, 7(1), 156. https://doi.org/10.1038/s41392-022-00994-0
4. Saeed, et al. (2023). Robotics and artificial intelligence and their impact on the diagnosis and treatment of cardiovascular diseases. International Journal of Surgery. https://pubmed.ncbi.nlm.nih.gov/37605683/
5. Samuel, A. J. (2024). Cloud security architectures for AI-enabled healthcare diagnostics and personalized treatment plans. World Journal of Advanced Engineering Technology and Sciences, 11(01), 467–484. https://doi.org/10.30574/wjaets.2024.11.1.0036
6. Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., … Albekairy, A. M. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. BMC Medical Education, 23(1), Article 298. https://doi.org/10.1186/s12909-023-04698-z
7. Grossi, M., Ibrahim, N., Rădescu, V., Loredo, R., Voigt, K., von Altrock, C., & Rudnik, A. (2022). Mixed quantum-classical method for fraud detection with quantum feature selection. arXiv. https://doi.org/10.48550/arXiv.2208.07963

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)

8. Innan, N., Sawaika, A., Dhor, A., Dutta, S., Thota, S., Gokal, H., Patel, N., & Bennai, M. (2023). Financial fraud detection using Quantum Graph Neural Networks. arXiv. https://doi.org/10.48550/arXiv.2309.01127
9. Kyriienko, O., & Magnusson, E. B. (2022). Unsupervised quantum machine learning for fraud detection. arXiv. https://doi.org/10.48550/arXiv.2208.01203
10. Fatunmbi, T. O. (2024). Advanced frameworks for fraud detection leveraging quantum machine learning and data science in fintech ecosystems. World Journal of Advanced Engineering Technology and Sciences, 12(1), 495–513. https://doi.org/10.30574/wjaets.2024.12.1.0057
11. Kyriienko, O., & Magnusson, E. B. (2022). Unsupervised quantum machine learning for fraud detection. arXiv. https://doi.org/10.48550/arXiv.2208.01203

Author: Olusoji John Samuel, University of Roehampton, London, United Kingdom.
Email : (soji.samuel@hustle.app)