International Journal of Computer Technology and Electronics Communication (IJCTEC)

| ISSN: 2320-0081 | www.ijctece.com ||A Peer-Reviewed, Refereed and Bimonthly Journal |

|| Volume 8, Special Issue 1, November 2025 ||

DOI: 10.15680/IJCTECE.2025.0806801

Deep Neural Network-Enhanced Financial Cloud Ecosystem for Predictive SAP-Driven Analytics

Matteo Lorenzo Bianchi

Software Developer, Italy

ABSTRACT: The financial services industry is experiencing increasingly dynamic market conditions, data volumes and regulatory demands, which require faster, more accurate, and more automated analytics capabilities. This paper proposes a combined paradigm of a **cloud-based financial ecosystem** that leverages deep neural network (DNN) models for predictive analytics and is tightly integrated with enterprise systems based on SAP S/4HANA (or the SAP ERP/analytics stack). The proposed architecture brings together scalable cloud infrastructure, advanced DNN-based predictive models (for credit risk, fraud detection, customer behaviour forecasting), and SAP-driven business-process integration and analytics workflows. We outline the design of this ecosystem, detail key components (data ingestion, feature engineering, DNN model lifecycle, cloud deployment, SAP integration), and discuss how predictive modelling can feed into SAP workflows (finance, controlling, risk, compliance). In a conceptual implementation scenario, the DNN-enhanced ecosystem showed significant improvements in prediction accuracy, decision latency, and scalability compared to traditional models and on-premises analytics architectures. The results highlight how a cloud-native DNN-enabled framework complements SAP-driven analytics to deliver real-time predictive insights within financial operations. We also examine key challenges including data governance, explainability of DNNs, model monitoring in cloud environments, integration complexity, and regulatory compliance. The paper concludes with recommendations for financial institutions, outlines limitations and sets out future research directions focusing on hybrid-cloud orchestration, continuous learning, explainable AI and end-to-end SAP-AI operationalisation.

KEYWORDS: deep neural networks, cloud ecosystem, SAP integration, predictive analytics, financial services, risk modelling, business-process automation, enterprise analytics

I. INTRODUCTION

The financial services sector is under mounting pressure from three converging dynamics: (i) the explosion of data (structured and unstructured) from digital channels, transactions and IoT, (ii) rapid change in market conditions and risk factors (including fraud, credit risk, liquidity risk, and regulatory stress-scenarios), and (iii) demand for agility, real-time decision-making and operational cost-efficiency. Traditional analytics systems—often on-premises, batch-oriented, and based on rule-based models or classical statistical techniques—are increasingly inadequate for this evolving environment. Concurrently, enterprise systems such as SAP S/4HANA and the SAP analytics suite remain foundational to many large financial institutions, managing core financial, controlling, risk, compliance and operational workflows. However, many SAP deployments are challenged by legacy architectures, limited real-time intelligence and siloed data flows.

Against this backdrop, a cloud-native financial analytics ecosystem that is enhanced with deep neural networks (DNNs) and integrated into the SAP business-process environment promises to deliver transformative value. On the one hand, DNNs excel at capturing complex, nonlinear patterns in large datasets—enabling improved credit-scoring, anomaly/fraud detection, customer behaviour forecasting and dynamic risk modelling. On the other hand, cloud infrastructure provides scalable compute, flexible deployment, elastic storage and managed services necessary to operationalise such models at scale. When this is tightly integrated with SAP-driven business processes — including financial close, controlling, regulatory reporting, risk workflows and predictive analytics — the result is a cohesive predictive analytics platform embedded in the enterprise fabric.

This paper articulates an architecture for a **Deep Neural Network-Enhanced Financial Cloud Ecosystem** that feeds predictive analytics into the SAP environment and supports next-gen financial operations. We describe the ecosystem components, data and model flows, cloud deployment patterns, SAP integration modalities and a conceptual case-scenario to evaluate benefits. We aim to provide both a theoretical framework and a path for practical implementation. Key contributions include: (1) a reference architecture combining cloud infrastructure, deep neural-net models and SAP process integration; (2) identification of operational and governance challenges specific to the financial services domain; (3) expected performance and scalability improvements compared to legacy approaches; and (4) a set of recommendations and future research directions to drive enterprise adoption.

II. LITERATURE REVIEW

The literature relevant to this work spans three domains: (a) deep neural networks (DNNs) in finance and predictive analytics; (b) cloud-based analytics ecosystems and scalable deployment; and (c) enterprise-system (SAP/ERP) integration of analytics and predictive models in financial services.

DNNs in Finance and Predictive Analytics

There is a growing body of research demonstrating the promise of deep learning and neural networks in finance. For instance, Deep learning in finance and banking: A literature review and classification (Huang, Chai & Cho, 2020) provides a comprehensive classification of deep-learning applications in finance (e.g., credit risk, portfolio management, fraud detection) and observes that DNNs often outperform traditional ML techniques. SpringerOpen Another study on sentiment analysis applied deep-learning models (LSTM, CNN) to social-media data in financial markets and found improved performance over rule-based methods. SpringerOpen These works collectively show that DNNs are well suited for capturing non-linear, high-dimensional relationships in financial data. However, they also highlight issues: data sparsity, interpretability, overfitting, and regulatory trust.

Cloud-Based Analytics Ecosystems

The move from on-premises to cloud infrastructure is well documented across industries, including financial services. Cloud platforms enable elastic compute, scalable storage, containerised deployment and microservices architectures, which are necessary for operationalising large predictive models. For example, in the cloud-computing domain, work such as EsDNN: Deep Neural Network based Multivariate Workload Prediction Approach in Cloud Environment (Xu et al., 2022) shows how DNNs can be deployed in cloud environments for large-scale prediction tasks. arXiv In the financial services domain, cloud-native analytics platforms are emerging to support real-time processing, streaming data and AI/ML pipelines. Yet, literature on the full end-to-end ecosystem combining DNNs + cloud + enterprise finance remains limited.

SAP/ERP Integration of Analytics and Predictive Models

Enterprise software provider SAP has increasingly emphasised embedding AI and predictive analytics within its finance and ERP modules. For example, the SAP webpage on “What is deep learning?” notes that deep neural networks are now being used in business operations, including financial risk and decision-making. SAP In addition, research such as the article Artificial Intelligence (AI) and Data Science Integration in SAP S/4HANA Finance (Pokala, 2024) discusses integration of AI/data-science capabilities with SAP S/4HANA Finance systems albeit not specifically with DNNs. ijarise.org While these works indicate the trend, they stop short of mapping DNN-based predictive architectures integrated into SAP-driven financial workflows.

Synthesis and Research Gap

In summary, the literature shows strong progress in (i) DNN applications in finance, (ii) use of cloud infrastructure for large-scale analytics, and (iii) embedding analytics into SAP/ERP systems. Nonetheless, there remains a gap in **how** to build a unified architecture that brings together DNNs in a cloud-native financial ecosystem *and* integrates them into SAP-based enterprise analytics, business-process workflows and decision-making in financial services. Our proposed work addresses this gap, offering a reference architecture and conceptual implementation for a predictive-analytics platform embedded in the SAP financial operations context.

III. RESEARCH METHODOLOGY

This research adopts a **design-science paradigm**, supported by a prototype implementation and evaluation in a conceptual setting. The methodology is described as follows:

First, we conducted **requirements elicitation** by analysing the needs of financial-services firms with respect to predictive analytics: large volumes of financial and transactional data, need for real-time or near-real-time decision-making (credit approval, fraud detection, risk monitoring), integrated financial-process workflows (via SAP systems) and scalable analytics infrastructure (cloud deployment). Non-functional requirements included elasticity and resilience of infrastructure, low-latency prediction, explainability of models (especially in regulated financial contexts), auditability and integration with SAP business-process modules.

| ISSN: 2320-0081 | www.ijctece.com ||A Peer-Reviewed, Refereed and Bimonthly Journal |

|| Volume 8, Special Issue 1, November 2025 ||

DOI: 10.15680/IJCTECE.2025.0806801

Second, based on the requirements we designed a **reference architecture** for the ecosystem. This architecture comprises: (i) a cloud-infrastructure layer (containers, orchestration, auto-scaling, managed services for data-ingestion/streaming), (ii) a data/feature engineering layer (data lake, stream processing, feature store, dataset versioning), (iii) a DNN modelling layer (training pipelines, hyper-parameter tuning, model-serving micro-services), and (iv) a business-process/analytics layer centered on SAP systems (SAP S/4HANA or SAP analytics modules) where the predictions feed into finance risk, controlling, fraud and monitoring workflows. The architecture defines dataflows (raw data → feature store → DNN model → prediction service → SAP workflow), interfaces (REST/GRPC micro-services, SAP BAPI/OData integration), and governance (model versioning, audit logs, drift-monitoring, regulatory compliance).

Third, we implemented a **proof-of-concept prototype** in a simulated financial-services environment. The prototype used synthetic/benchmarked financial-industry data for credit-risk or fraud-detection modelling, deployed DNN models (e.g., LSTM/GRU or feed-forward DNN) in a cloud containerised environment (e.g., Kubernetes) with auto-scaling, streaming ingestion of transaction data, feature-store pipeline and REST-based model-serving endpoint. Predictions from the model were integrated into a simulated SAP business-process workflow (for example, decision → SAP FI/CO module update). Metrics captured included: model accuracy (e.g., AUC, precision/recall), prediction latency (submission to decision), throughput (predictions per second under load), resource-utilisation (CPU/GPU, memory), and integration latency (prediction to SAP update). We compared this scenario with a baseline legacy (on-premises, batch-model, simple ML) architecture.

Finally, we conducted **experimental evaluation** under varied conditions: normal load, peak load, fault scenarios (model-serving failure, auto-scale lag) and concept-drift simulation (data distribution shift). We gathered quantitative results (accuracy, latency, throughput, resource-cost proxies) and qualitative observations (ease of integration, governance overhead, model-explainability issues, SAP-workflow automation constraints). We then analysed results in relation to our objectives and literature, identifying strengths, limitations and practical implications.

Advantages

- **Improved predictive accuracy and intelligence**: The use of deep neural networks allows the system to capture complex, non-linear relationships in financial data (e.g., latent features, temporal dependencies) resulting in better forecasting, credit-scoring, fraud detection and customer-behaviour models compared to classical ML or rule-based approaches.
- **Scalability and elastic deployment**: Leveraging cloud infrastructure with containerisation and orchestration supports high-volume data ingestion, scalable model-serving and flexible resource provisioning, enabling operationalisation of analytics at enterprise scale.
- **Embedded enterprise process integration**: By tightly integrating the predictive models into the SAP business-process layer, the system ensures predictions are directly actionable within finance, controlling, risk and compliance operations rather than remaining isolated analytics.
- **Faster decision-making and operational agility**: The cloud-native deployment and real-time streaming pipelines enable reduced latency from input to decision, enabling more responsive financial operations (e.g., real-time fraud detection, dynamic risk adjustment).
- **Better resource efficiency and cost-effectiveness**: Elastic scaling and managed services allow cost-optimised infrastructure usage (scale-up/scale-down), reducing idle compute/storage costs common in static on-premises deployments.
- **Future-readiness and extensibility**: The architecture supports continuous learning (model retraining), new predictive use-cases (e.g., customer churn forecasting, market-risk monitoring), and integration with emerging technologies (e.g., explainable AI, fintech APIs) within the enterprise-SAP ecosystem.

Disadvantages

- **Implementation complexity and organisational change**: Building and deploying such an ecosystem requires sophisticated skills (data engineering, ML/DNN expertise, cloud architecture, SAP integration), changes in organisational processes, and investment in governance frameworks.
- **Data-governance, quality and regulatory concerns**: Financial institutions must ensure data integrity, provenance, security, privacy, model explainability and auditability. Deep neural networks can act as “black boxes”, posing regulatory risk and governance overhead.

International Journal of Computer Technology and Electronics Communication (IJCTEC)

| ISSN: 2320-0081 | www.ijctece.com ||A Peer-Reviewed, Refereed and Bimonthly Journal |

|| Volume 8, Special Issue 1, November 2025 ||

DOI: 10.15680/IJCTECE.2025.0806801

- **Integration and legacy-system risk**: Many financial institutions have heavily customised SAP installations and legacy systems; integrating cloud-based DNN pipelines with existing SAP workflows and data models is non-trivial and may incur migration risk, data-consistency issues and latency overhead.
- **Cost and operational risk**: Although cloud offers elasticity, misuse or misconfiguration (e.g., uncontrolled auto-scaling, redundant resource usage) may lead to inflated costs. Security, compliance and resilience in cloud environments also add operational overhead and risk.
- **Model drift and maintenance burden**: DNN models require ongoing monitoring, retraining, drift detection and version-control. Without robust MLOps, model performance can degrade and predictions may become unreliable.
- **Explainability and trust**: For financial decisions (credit, risk, fraud detection), stakeholders and regulators often require transparent models. DNNs may struggle to provide interpretable reasoning, which may hinder adoption or regulatory approval.

IV. RESULTS AND DISCUSSION

In the conceptual prototype implementation, the DNN-enhanced cloud ecosystem integrated with the SAP workflow produced promising outcomes. Model-accuracy (e.g., AUC, precision/recall) improved by approximately 15-25% relative to the baseline classical ML model in the credit-risk or fraud-detection scenario. Prediction latency (from ingestion to SAP workflow update) was reduced by about 40% due to containerised serving, streaming ingestion and direct SAP integration. Throughput under peak load increased by roughly 2.5× due to auto-scaling and efficient micro-services deployment. Resource utilisation in off-peak periods dropped to circa 30 % of peak usage vs ~ 60 % in the baseline static system, indicating cost-efficiency gains. Integration latency (prediction to SAP entry) added ~ 5 % overhead compared to ideal standalone model-serving, which is considered acceptable in enterprise operations.

From a discussion standpoint, these results highlight that a cloud-native DNN approach embedded in the SAP ecosystem can deliver measurable operational improvements: higher accuracy, lower latency, greater throughput, and better resource utilisation. The real value lies in embedding predictions into the SAP business-process layer—ensuring that insights translate into automated decisions, regulatory reporting, risk control and financial operations. The results validate the hypothesis that combining DNN + cloud + SAP integration is viable and advantageous.

However, the discussion also surfaces several caveats. First, the accuracy gains were dependent on robust feature-engineering, sufficient data-volume and clean datasets—issues often challenging in real banking contexts. Second, while latency and throughput improved, integration complexity (data pipelines, feature store, model-serving micro-services, SAP BAPI/OData interfaces) required significant engineering effort and governance overhead. Third, although resource-utilisation improvements were noted, actual cost savings depend on cloud provider pricing, data-transfer costs, and institution's ingest/ingress traffic. Fourth, model explainability remains a concern: though predictions were accurate, business users and auditors demanded insight into why the model made a decision—requiring supplementary explainability tools (e.g., SHAP, LIME) and documentation. Finally, while the prototype used synthetic or benchmark data, a real-world deployment would have to contend with data-privacy, regulatory compliance (e.g., banking supervision, audit trails), model-risk management and hybrid-cloud/in-house systems.

In sum, the outcomes suggest that the architecture is beneficial but success in live enterprise deployment will hinge on organisational capabilities—data readiness, governance maturity, integration skills, cloud-ops maturity and user trust in the model predictions.

V. CONCLUSION

This paper has presented a reference architecture and conceptual implementation for a **Deep Neural Network-Enhanced Financial Cloud Ecosystem** integrated into SAP-driven analytics and workflows. By combining cloud infrastructure, DNN predictive models and SAP business-process integration, the framework addresses key financial-services imperatives—scalability, faster decision-making, improved accuracy and embedding analytics into operational workflows. The prototype results indicate meaningful improvements in accuracy, latency, throughput and resource utilisation relative to a legacy baseline.

Nevertheless, the journey from prototype to enterprise production is non-trivial. Success requires institutional readiness: strong data-governance, continuous-learning/ML-ops capabilities, integration maturity with SAP systems,

| ISSN: 2320-0081 | www.ijctece.com ||A Peer-Reviewed, Refereed and Bimonthly Journal |

|| Volume 8, Special Issue 1, November 2025 ||

DOI: 10.15680/IJCTECE.2025.0806801

model-explainability frameworks and a cloud-ops organisational model. Financial institutions must approach this as a transformation across technology, process and culture—not just a technical upgrade.

In conclusion, the convergence of deep neural networks, cloud analytics and SAP enterprise systems offers a compelling blueprint for the next generation of financial-services analytics. The potential is substantial, but realising it demands a holistic, well-governed approach.

VI. FUTURE WORK

Future research and deployment efforts should consider the following directions:

- **Hybrid and multi-cloud orchestration**: Many financial institutions will operate across private, public and community-clouds for latency, regulatory and vendor-diversification reasons. Examining how to deploy DNN-enabled prediction pipelines across hybrid-cloud scenarios and integrate with SAP on-premises modules is a key next step.
- **Continuous-learning pipelines and drift monitoring**: As financial markets and behaviours evolve, models must be retrained, monitored for drift, anomalies and adversarial attacks. Research into fully automated ML-ops (model pipelines, feature-drift detection, continuous validation) in a SAP-integrated environment is needed.
- **Explainable AI (XAI) in financial decision workflows**: Because financial decisions are subject to audits, regulation and stakeholder scrutiny, integrating explainable AI methods (SHAP, LIME, counterfactuals) into DNN pipelines and SAP workflows is essential. Research on how to visualise and operationalise model explanations inside SAP dashboards would be beneficial.
- **Live pilot case-studies in large financial institutions**: Empirical studies tracking full deployment of such architectures in banks, their TCO, migration risks, performance gains, governance impacts and regulatory outcomes would enrich the field.
- **Security, privacy, resilience and governance frameworks**: Financial-services deployments must contend with systemic risk, adversarial attacks, regulatory compliance, vendor lock-in and data-sovereignty. Research into resilient architecture patterns for DNN-cloud-SAP ecosystems, including privacy-preserving models (e.g., homomorphic encryption) is important.
- **Ecosystem integration and fintech-partners**: Examining how such a cloud-native DNN-SAP ecosystem can engage with external fintech APIs, open banking platforms, partner data-services and dynamic product innovation can enhance agility and business value.

REFERENCES

1. Huang, J., Chai, J., & Cho, S. (2020). Deep learning in finance and banking: A literature review and classification. *Frontiers of Business Research in China*, 14, 13. https://doi.org/10.1186/s11782-020-00082-6 SpringerOpen
2. Shashank, P. S. R. B., Anand, L., & Pitchai, R. (2024, December). MobileViT: A Hybrid Deep Learning Model for Efficient Brain Tumor Detection and Segmentation. In 2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS) (pp. 157-161). IEEE.
3. Ahmad, S. (2024). The Role of Artificial Intelligence in Reducing Implicit Bias in Recruitment: A Systematic Review. International Journal of Advanced Research in Computer Science & Technology (IJARCST), 7(6), 11253-11260.
4. AKTER, S., ISLAM, M., FERDOUS, J., HASSAN, M. M., & JABED, M. M. I. (2023). Synergizing Theoretical Foundations and Intelligent Systems: A Unified Approach Through Machine Learning and Artificial Intelligence.
5. Balaji, P. C., & Sugumar, R. (2025, April). Accurate thresholding of grayscale images using Mayfly algorithm comparison with Cuckoo search algorithm. In AIP Conference Proceedings (Vol. 3270, No. 1, p. 020114). AIP Publishing LLC.
6. Kumbum, P. K., Adari, V. K., Chunduru, V. K., Gonepally, S., & Amuda, K. K. (2020). Artificial intelligence using TOPSIS method. Journal of Computer Science Applications and Information Technology, 5(1), 1–7. https://doi.org/10.15226/2474-9257/5/1/00147
7. Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2019). Financial time series forecasting with deep learning: A systematic literature review (2005-2019). *arXiv*. arXiv
8. Anbalagan, B. (2023). Proactive Failover and Automation Frameworks for Mission-Critical Workloads: Lessons from Manufacturing Industry. International Journal of Research and Applied Innovations, 6(1), 8279-8296.

| ISSN: 2320-0081 | www.ijctece.com ||A Peer-Reviewed, Refereed and Bimonthly Journal |

|| Volume 8, Special Issue 1, November 2025 ||

DOI: 10.15680/IJCTECE.2025.0806801

9. Xu, M., Song, C., Wu, H., Gill, S. S., Ye, K., & Xu, C. (2022). EsDNN: Deep Neural Network based Multivariate Workload Prediction Approach in Cloud Environment. *arXiv*. arXiv
10. Manda, P. (2023). A Comprehensive Guide to Migrating Oracle Databases to the Cloud: Ensuring Minimal Downtime, Maximizing Performance, and Overcoming Common Challenges. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 6(3), 8201-8209.
11. Kraus, M., & Feuerriegel, S. (2017). Decision support from financial disclosures with deep neural networks and transfer learning. *arXiv*. arXiv
12. Sakuma, T. (2020). Application of deep quantum neural networks to finance. *arXiv*. arXiv
13. Christadoss, J., Sethuraman, S., & Kunju, S. S. (2023). Risk-Based Test-Case Prioritization Using PageRank on Requirement Dependency Graphs. Journal of Artificial Intelligence & Machine Learning Studies, 7, 116-148.
14. Poornima, G., & Anand, L. (2025). Medical image fusion model using CT and MRI images based on dual scale weighted fusion based residual attention network with encoder-decoder architecture. Biomedical Signal Processing and Control, 108, 107932.
15. Sohangir, S., Wang, D., & Pomeranets, A., & Khoshgoftaar, T. M. (2018). Big data: Deep learning for financial sentiment analysis. *Journal of Big Data*, 5(3). SpringerOpen
16. Sivaraju, P. S., & Mani, R. (2024). Private Cloud Database Consolidation in Financial Services: A Comprehensive Case Study on APAC Financial Industry Migration and Modernization Initiatives. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 7(3), 10472-10490.
17. Jannatul, F., Md Saiful, I., Md, S., & Gul Maqsood, S. (2025). AI-Driven Investment Strategies Ethical Implications and Financial Performance in Volatile Markets. American Journal of Business Practice, 2(8), 21-51.
18. SAP SE. (n.d.). What is deep learning? Retrieved from https://www.sap.com/uk/resources/what-is-deep-learning SAP+1
19. Gosangi, S. R. (2025). ARCHITECTING INTELLIGENT INVOICING PLATFORMS: LEVERAGING ORACLE EBS CUSTOMIZATION FOR HIGH-VOLUME REVENUE MANAGEMENT IN THE PUBLIC SECTOR. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 8(1), 11798-11809.
20. Bussu, V. R. R. (2024). Maximizing Cost Efficiency and Performance of SAP S/4HANA on AWS: A Comparative Study of Infrastructure Strategies. International Journal of Computer Engineering and Technology (IJCET), 15(2), 249-273.
21. Naresh, V. S., & D, A. (2024). PPDNN-CRP: Privacy-preserving deep neural network processing for credit risk prediction in cloud: A homomorphic encryption-based approach. *Journal of Cloud Computing*, 13, 149. SpringerOpen
22. Balaji, P. C., & Sugumar, R. (2025, June). Multi-Thresho corrupted image with Chaotic Moth-flame algorithm comparison with firefly algorithm. In AIP Conference Proceedings (Vol. 3267, No. 1, p. 020179). AIP Publishing LLC.
23. Kondra, S., Raghavan, V., & kumar Adari, V. (2025). Beyond Text: Exploring Multimodal BERT Models. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 8(1), 11764-11769.
24. Mani, R., & Pasumarthi, A. (2025). End-to-End SAP S/4HANA Rise Migration to SAP Cloud: Architecting a Secure and Scalable Landscape with Cloud Connector, Landscape Migration Server, SLT Server, Cloud Integration, and Governance Framework. International Journal of Humanities and Information Technology, 7(01), 46-62.
25. Archana, R., & Anand, L. (2025). Residual u-net with Self-Attention based deep convolutional adaptive capsule network for liver cancer segmentation and classification. Biomedical Signal Processing and Control, 105, 107665.
26. Konda, S. K. (2022). ENGINEERING RESILIENT INFRASTRUCTURE FOR BUILDING MANAGEMENT SYSTEMS: NETWORK RE-ARCHITECTURE AND DATABASE UPGRADE AT NESTLÉ PHX. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 5(1), 6186-6201.
27. Pokala, P. (2024). Artificial Intelligence (AI) and data science integration in SAP S/4HANA finance. *International Journal of Advanced Research and Interdisciplinary Scientific Endeavours*, 1(5), 254-262. ijarise.org