ISSN Online : 2709-5088
ISSN Print : 2709-507X

INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND TECHNOLOGY (IJCST) Vol. 7 No. 1 (2023)

Exploring Advanced Techniques for Agricultural Area Mapping: Comparative Analysis of U-Net and Mask-Based Approaches in Satellite Imagery

1st Ahmad Iqbal

Research and Development Punjab IT Board, Lahore, PK ahmad.iqbal@pitb.gov.pk

2nd Saad Bin Zahid

Research and Development Punjab IT Board, Lahore, PK saad.zahid@pitb.gov.pk

3rd Javeria Iqbal

California institute of arts and technology Department of Computer Science California, US, Jiqbal@ciat.edu

4th Adeel Khalil

GIS Development 4EI, London, UK adeel.khalil@4ei.com

***Abstract*:**

Deep learning methodologies have rapidly gained prominence in the realm of statistical analysis for remote sensing data. These techniques are instrumental in processing spectral information, conducting identification statistics, and performing segmentation and classification of objects in satellite imagery. Image segmentation enhances the accuracy of object statistics by effectively distinguishing objects from their backgrounds. This paper delves into the application of Mask Based Approaches and U-Net in satellite imagery segmentation. An experimental study is conducted to evaluate the suitability of these models in this domain. The experimental results, measured in terms of mean average precision (mAP), indicate a remarkable performance, with a precision of 93.21% for Mask-Bcoased Approaches and 90.69% for U-Net, based on a dataset comprising satellite images of Pakistan. These findings underscore the potential of these techniques in advancing the accuracy and efficiency of object segmentation in satellite imagery analysis.

***Keywords*:** Unet, Machine Learning, Satellite Imagery, Segmentation, Agriculture

INTRODUCTION

Satellite imagery or remote sensing imagery refers to data collected from satellites, civil aircraft, dedicated aircraft, or drones, utilizing sensors and video cameras to capture objects on the Earth's surface [1]. These images are crucial for various scientific studies, such as weather forecasting, natural disaster prediction, geological studies [2], forestry monitoring, and agricultural applications. In agriculture, remote sensing plays a significant role in management, statistics, and farming activities [3]. It enables tasks like agricultural production forecasting, geographic information analysis, agricultural map- ping, deforestation warning, and vegetation index monitoring [4]. Deep learning, a subset of artificial intelligence, has revo- lutionized several fields since 2012 [5, 6], including healthcare, data processing, and image recognition. Deep learning models, inspired by the human neural network, excel in information processing and transmission, making them faster and more ac- curate in solving complex problems [7]. Agricultural satellite image processing is one area where deep learning methods are applied to identify and segment agricultural objects in satellite images [8, 9]. Despite the advancements, there is limited research comparing the effectiveness of different deep learning models in agricultural area segmentation, especially in developing countries like Pakistan [10]. Pakistan, being the second-largest rice exporter globally and with agriculture contributing significantly to its GDP, presents a unique case for studying agricultural practices in Eastern countries [11-13]. In this study, we focus on comparing two prominent models, Mask and U-Net, for agricultural area segmentation in satellite images [14]. Mask, an extension of Faster, incorporates a mask layer for object segmentation [15]. U-Net, initially designed for biomedical object segmentation, has shown high efficiency in various fields, including satellite image segmentation [16, 17]. This research aims to assess the effectiveness of Mask and U-Net in agricultural remote sensing. The experiments are conducted on datasets from both Pakistan and other regions (The Americas or Europe) [18], providing insights into the models' accuracy in different agricultural settings. By evalu- ating these models on Eastern agricultural areas, particularly in Pakistan, this study contributes

ISSN Online : 2709-5088
ISSN Print : 2709-507X
IJCST

valuable knowledge about their applicability in diverse contexts. In this research study, we investigated the application of two advanced models, Mask and U-Net, for agricultural image segmentation on satellite imagery. The paper is organized into six main sections. The first section provides an overview of the research, outlining its scope and objectives. In the second section, we delve into the current landscape of deep learning applications in agricultural satellite image processing. The third section details the methodologies employed for utilizing the Mask and U-Net models in segmenting agricultural areas on satellite images. Moving on, the fourth section elaborates on the specific train- ing processes conducted for these models. In the fifth section, we present the results obtained from the application of Mask and U-Net to real agricultural satellite images, highlighting the accuracy of each model and offering a comprehensive com- parison of their effectiveness in agricultural area segmentation. Finally, the sixth section concludes the study, summarizing the findings, and discusses potential directions for future research and development in this field.

I. DEEP LEARNING IN AGRICULTURAL SATELLITE IMAGE SEGMENTATION

Agricultural satellite imagery processing presents a spec- trum of challenges, ranging from basic object classification to more complex tasks like object detection and segmentation [19]. Previous studies have utilized various deep learning models to address these challenges [20, 21. 22]. For instance,

P. Helber [23] and colleagues successfully employed a deep learning model to classify 10 different land objects with remarkable accuracy exceeding 96[24]. Chang et al integrated object classification and detection, specifically identifying di- verse forest types, showcasing the potential of deep learning methods in this domain. Object segmentation, a higher-level processing task, involves delineating objects from background data, enabling precise analysis. Several models have been explored in this context [25,26]. K.M. Masoud experimented with the improved FCN model, achieving certain effectiveness in agricultural area segmentation [27]. However, complex architectures like FCN require substantial computational re- sources [28]. U-Net, a simpler yet efficient model, has gained traction in agricultural satellite image segmentation [29]. Stud- ies by Andrei Stoian applied U-Net to segment soil distribu- tions, demonstrating its effectiveness, albeit with a focus on multiple object types [30]. Mask models, akin to Mask, have shown promise in solving object recognition problems. W. Zhang successfully employed Mask based approaches to seg- ment Arctic glaciers, achieving an impressive Mean Average Precision (mAP) accuracy of 70various object segmentation tasks, its potential in agricultural area segmentation remains relatively unexplored [31]. Comparative evaluations between models such as Mask and U-Net have been conducted in specific contexts. However, in the realm of agricultural area segmentation, a comprehensive and generalized comparison between these models is lacking. In our research, we aim to bridge this gap by conducting an in-depth analysis and comparison of the effectiveness of Mask models and U-Net in agricultural satellite image segmentation, particularly in complex agricultural areas.

EXPERIMENTAL PROCESS

The experimental process comprises six main steps.

1) *Data Collection::* We meticulously curated our dataset by capturing 24000 images of agricultural areas in Pakistan and other countries using Google Maps and Microsoft's Snipping tool. Ensuring a diverse range of object categories was essential to impart the necessary attributes for effective learning.

2) *Assigning Data Labels::* Utilizing the VGG Image An- notator tool, we assigned precise location labels to objects in the dataset photos. Accurate data labeling is pivotal as the model relies on these annotations during training. Incorrect labels could hinder the model's ability to grasp object proper- ties, leading to inaccurate predictions.

A. *Model Training:*

The core of the training process involved feeding the model with labeled data to extract object features. Different models have unique learning styles, requiring careful adjustment of learning parameters to achieve

ISSN Online : 2709-5088
ISSN Print : 2709-507X
IJCST

optimal results. Training in- volved enabling the model to recognize and confirm objects in unseen images

B. *Model Testing:*

Testing assessed the model's learning progress. If the model did not perform as expected, we refined the data or adjusted learning parameters. Evaluation was based on predicted results in images and learning curve graphs. Choosing the optimal model depended on several factors, including problem require- ments, dataset criteria, and object features.

C. *IMPLEMENTATION AND TRAINING*

Based on the data from step 4 and accurate model mea- surements, we compared the experimental models against theoretical expectations. A detailed evaluation was conducted, comparing the quality and effectiveness of both models in segmenting the same images. This assessment gauged the models' performance in solving agricultural area segmentation challenges in satellite imagery

D. *Processing Predicted Results:*

In this step, we post-processed the test model results to enhance accuracy. False predictions were eliminated, missing predictions added, and inaccurate ones refined. This refinement improved segmentation values, making them more reliable for various applications, including generating new training datasets and agricultural area statistics. A higher degree of accuracy in images enhanced their reliability for statistical analysis

II. IMPLEMENTATION AND TRAINING

A. Training Data

In remote sensing, the accuracy of information collection devices significantly impacts the reliability of subsequent anal- ysis. However, these devices can be costly. Given our limited research funding, we opted for readily available free satellite image sources. We utilized Google Maps, a versatile software offering satellite views with adjustable altitudes (ranging from 5m to 2000km). Our dataset was meticulously curated from Google Maps' public domain. During data collection, we ensured that each selected image contained at least one object, with over 50% of the image representing the agricultural land to be segmented. Objects, such as tree shadows, tractors, and wells, were carefully labeled, while confusing data was restricted. The number of objects in each image varied between 1 to 20.

Our dataset comprises 24000 images, divided into two categories: satellite images of agricultural areas in Pakistan and those from other regions. The images predominantly focus on key agricultural areas. In the Pakistan dataset, approximately 75% of images are from the southern region, 20% from the northern region, and 5% from the central region. The Non- Pakistan dataset consists of 40% images from America, 40% from Europe, 15% from Africa, and 5Pakistan's unique geographical features, including its intricate river network, pose challenges. Agricultural satellite images in this area often contain various interfering objects such as houses, rivers, lakes, and canals. Moreover, the characteristics of the river network influence agricultural land planning, leading to diverse shapes and sizes of agricultural lands in Pakistan. The limited application of high technology, like segmenting agricultural areas using commercial satellites, further complicates obtain- ing a comprehensive set of agricultural images from different regions in Pakistan.

III. RESULT AND EVALUATION

In the evaluation of the Mask and U-Net models on agricul- tural datasets from Pakistan and other regions, several key ob- servations were made. The training process for Mask exhibited an initial decrease in error followed by an increase due to over- fitting, caused by a high learning rate and an excessive number of training steps. Early stopping was implemented to mitigate this issue, selecting the model with the lowest error for eval- uation. The evaluation was conducted using Intersection over Union (IoU), precision, recall, and mean Average Precision (mAP) metrics. For Mask, the evaluation results showed that Mask based Non-Pakistan outperformed Mask Pakistan. This superiority was

ISSN Online : 2709-5088
ISSN Print : 2709-507X
IJCST

attributed to the larger training dataset used for Non Pakistan, leading to better model performance. The IoU values for Mask Non-Pakistan (0.8070) were higher than those for Mask Pakistan (0.7980), indicating better accuracy in predicting object overlaps. Similarly, precision and recall val- ues were better for Mask Non-Pakistan, demonstrating higher accuracy in model projections and reduced omission of correct objects, respectively. The mAP parameter, which measures prediction accuracy, was significantly higher for Mask Non- Pakistan (0.9521) compared to Mask Pakistan (0.8574). In the case of U-Net, the training error decreased steadily over time. The evaluation was carried out using IoU, Dice coefficient, and mAP metrics. U-Net Non-Pakistan outperformed U-Net Pakistan, showcasing the impact of a larger training dataset. The IoU value for U-Net Non Pakistan (0.8302) was higher than that for U-Net Pakistan (0.7284), indicating improved accuracy in predicting object overlaps. The Dice coefficient, which evaluates accuracy based on the overlap of predicted values and correct object labels, also demonstrated superior performance for U-Net Non-Pakistan (0.9048) compared to U- Net Pakistan (0.8368). Additionally, the mAP parameter was significantly higher for U-Net Non-Pakistan(0.9269) compared to U-Net Pakistan (0.7924). Comparing the two models, it was evident that the quantity and quality of training data signifi- cantly influenced the performance of both Mask and U-Net. Although the agricultural areas in Pakistan exhibited lower sharpness, leading to challenges in learning object attributes and potential confusion with other objects, the deviations in evaluation parameters between Pakistan and Non Pakistan datasets were not substantial within each model. This suggests that deep learning models, including Mask and U-Net, can effectively handle agricultural area segmentation in satellite imagery, and their performance is consistent across different regions.

IV. CONCLUSION AND FUTURE WORK

In this study, we explored the effectiveness of two image segmentation models, Mask and U-Net, for segmenting agri- cultural land in Pakistan. Our experiment utilized a satellite image dataset extracted from Google Maps, emphasizing the influence of image quality on model performance. U-Net, originally designed for high-quality medical data, exhibited enhanced efficiency when trained on the Non-Pakistan dataset, which featured higher-quality images compared to the Pakistan dataset. Both models demonstrated high accuracy when ap- plied to agricultural areas in Pakistan and other global regions, as evidenced by the model evaluation metrics. This involves addressing false predictions, refining inaccurate ones, and filling in missing predictions. By combining model-generated predictions with manual results, we aim to create a dataset that is accurate and reliable. These enhanced datasets will not only improve the training of our models but also streamline the complexities associated with manual data labeling. Addi- tionally, the refined datasets can find practical applications in various areas, including remote sensing support for land area statistics, mapping, and related fields.

REFERENCES

[1] Satellite Imaging Corporation, https://www.satimagingcorp.com, last ac- cessed 2020/02/20.

[2] Planet, https://www.planet.com/markets/monitoring-for-precision- agriculture/, last accessed 2020/02/20.

[3] Liu, L., Ouyang, W., Wang, X., Fieguth, P., Chen, J., Liu, X., Pietik äinen, M: Deep learning for generic object detection: A survey. International Journal of Computer Vision vol 128, pp. 261-318. Semanticscholar (2020).

[4] Dargan, S., Kumar, M., Ayyagari, M.R. et al: A Survey of Deep Learning and Its Applications: A New Paradigm to Machine Learning. Arch Computat Methods Eng (2019).

[5] Marktechpost, https://www.marktechpost.com/2019/04/18/introduction- to-neural-networks-advantages-and-applications/, last accessed 2020/02/20.

[6]L. Jiao et al.: A Survey of Deep Learning-Based Object Detection: In IEEE Access, vol. 7, pp. 128837-128868. IEEE (2019).

[7] Minaee, S., Boykov, Y., Porikli, F., Plaza, A., Kehtarnavaz, N., Terzopou- los, D., Image Segmentation Using Deep Learning: A Survey. ArXiv, abs/2001.05566 (2020).

[8] Helber, P., Bischke, B., Dengel, A., Borth, D.: EuroSAT: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification. IEEE Journal of Selected Topics in Applied Earth Obser- vations and Remote Sensing, vol 12, pp. 2217-2226 (2017).

[9] Chang, T., Rasmussen, B.P., Dickson, B.G.,Zachmann, L.J.: Chimera: A Multi-Task Recurrent Convolutional Neural Network

for Forest Classi- fication and Structural Estimation. Remote Sensing, vol 11 (7), pp.768 (2019).

[10]E. Charou: Deep Learning for Agricultural Land Detection in Insular Areas. 10th International Conference on Information, Intelligence, Sys- tems and Applications (IISA), PATRAS, Greece, pp. 1-4. IEEE (2019).

[11] Masoud, K.M.; Persello, C.; Tolpekin, V.A: Delineation of Agricul- tural Field Boundaries from Sentinel-2 Images Using a Novel Super- Resolution Contour Detector Based on Fully Convolutional Networks. Remote Sens vol 12 (1), pp. 59 (2020).

[12] Yang, M.-D.; Tseng, H.-H.; Hsu, Y.-C.; Tsai, H.P: Semantic Segmen- tation Using Deep Learning with Vegetation Indices for Rice Lodging Identification in Multi-date UAV Visible Images. Remote Sens vol 12, pp. 633 (2020).

[13] He, K., Gkioxari, G., Doll ár, P., Girshick, R.B.: Mask R-CNN. 2017 IEEE International Conference on Computer Vision (ICCV), pp. 2980- 2988 (2017).

[14] Zhang, W.; Witharana, C.; Liljedahl, A.K.; Kanevskiy, M. Deep Con- volutional Neural Networks for Automated Characterization of Arctic Ice-Wedge Polygons in Very High Spatial Resolution Aerial Imagery. Remote Sens, vol 10, pp. 1487 (2018).

[15] Chen, L., Xie, T., Wang, X., Wang, C.: Identifying urban villages from city-wide satellite imagery leveraging mask R-CNN. In: Ju Z., Yang L., Yang C., Gegov A., Zhou D. (eds) Advances in Computational Intelligence Systems. UKCI 2019. Advances in Intelligent Systems and Computing, vol 1043, pp 29. Springer, Cham (2019).

[16] International Conf. on Computer Vision ICCV 2019, http://cocodataset.org/workshop/coco-mapillary-iccv-2019.html, last accessed 2020/02/20.

[17] Dai, J., He, K., Sun, J.: Instance-Aware Semantic Segmentation via Multi-task Network Cascades. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3150-3158 (2015).

[18] Li, Y., Qi, H., Dai, J., Ji, X., Wei, Y.: Fully Convolutional Instance- Aware Semantic Segmentation. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 4438-4446 (2016).

[19] Ronneberger, O., Fischer, P., Brox, T.: U-Net: Convolutional Networks for Biomedical Image Segmentation. In: Navab N., Hornegger J., Wells W., Frangi A. (eds) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. MICCAI 2015. Lecture Notes in Com- puter Science, vol 9351. Springer, Cham (2015).

[20] Fang, W., Fu, L., Zhang, M., Li, Z.: Seismic data interpolation based on U-Net with texture loss. ArXiv, abs/1911.04092 (2019).

[21] Chen, J., Viquerat, J., Hachem, E.: U-Net architectures for fast prediction of incompressible laminar flows. Semanticscholar(2019).

[22] Souza R Bento, M.P., Nogovitsyn, N. Chung, K., Lebel, R.M., Frayne, R.: Dual-domain Cascade of U-Nets for Multi-channel Magnetic Reso- nance Image Reconstruction. ArXiv, abs/1911.01458 (2019).

[23] Iglovikov, V.I., Shvets, A: TernausNet: U-Net with VGG11 Encoder Pre- Trained on ImageNet for Image Segmentation. ArXiv, abs/1801.05746 (2018).

[24] Yi, Y., Zhang, Z., Zhang, W., Zhang, C., Li, W., Zhao, T.: Semantic Segmentation of Urban Buildings from VHR Remote Sensing Imagery Using a Deep Convolutional Neural Network. Remote Sen vol 11 (5), pp. 1774 (2019).

[25]E. Charou: Deep Learning for Agricultural Land Detection in Insular Areas: In 10th International Conference on Information, Intelligence, Systems and Applications (IISA), pp. 1-4, PATRAS, Greece (2019).

[26] Stoian, A., Poulain, V., Inglada, J., Poughon, V., Derksen: D. Land Cover Maps Production with High Resolution Satellite Image Time Series and Convolutional Neural Networks: Adaptations and Limits for Operational Systems. Remote Sens vol 11 (17), pp. 1986 (2019).

[27] Qadir, H., Shin, Y., Solhusvik, J., Bergsland, J., Aabakken, L., Bal- asingham, I.:Polyp Detection and Segmentation using Mask R-CNN: Does a Deeper Feature Extractor CNN Always Perform Better?. In 13th International Symposium on Medical Information and Communication Technology (ISMICT), pp. 1-6 (2019).

[28] Minkesh, A., Worranitta, K.,Taizo, M.: Human Extraction and Scene Transition utilizing Mask R-CNN. ArXiv, abs/1907.08884 (2019).

[29] Tiebiao Zhao; Yonghuan Yang; HaoyuNiu; Dong Wang; YangQuan Chen: Comparing U-Net convolutional network with mask R-CNN in the performances of pomegranate tree canopy segmentation. Proceedings Volume 10780, Multispectral, Hyperspectral, and Ultraspectral Remote Sensing Technology, Techniques and Applications VII; 107801J (2018). SPIE Asia-Pacific Remote Sensing, Honolulu, Hawaii, United States (2018).

[30] Dutta, A., Gupta, A., Zisserman, A.: VGG Image Annotator (VIA), http://www.robots.ox.ac.uk/ vgg/software/via/, last accessed 2020/02/20.

[31] Hui, J.: mAP (mean Average Precision) for Object Detection, https://medium.com/@jonathanhui/map-mean-average-precision-for- object-detection-45c121a31173, last accessed 2020/02/20.

ISSN Online : 2709-5088
ISSN Print : 2709-507X
IJCST

[32] Liang, J., Wang, R., Liu, X., Yang, L., Zhou, Y., Cao, B., & Zhao, K. (2021, July). Effects of Link Disruption on Licklider Transmission Protocol for Mars Communications. In *International Conference on Wireless and Satellite Systems* (pp. 98-108). Cham: Springer International Publishing.

[33] Liang, J., Liu, X., Wang, R., Yang, L., Li, X., Tang, C., & Zhao, K. (2023). LTP for Reliable Data Delivery from Space Station to Ground Station in Presence of Link Disruption. *IEEE Aerospace and Electronic Systems Magazine*.

[34] Arif, H., Kumar, A., Fahad, M., & Hussain, H. K. (2023). Future Horizons: AI-Enhanced Threat Detection in Cloud Environments: Unveiling Opportunities for Research. *International Journal of Multidisciplinary Sciences and Arts*, *2*(2), 242-251.

[35] Kumar, A., Fahad, M., Arif, H., & Hussain, H. K. (2023). Synergies of AI and Smart Technology: Revolutionizing Cancer Medicine, Vaccine Development, and Patient Care. *International Journal of Social, Humanities and Life Sciences*, *1*(1), 10-18.

[36] Yang, L., Liang, J., Wang, R., Liu, X., De Sanctis, M., Burleigh, S. C., & Zhao, K. (2023). A Study of Licklider Transmission Protocol in Deep-Space Communications in Presence of Link Disruptions. *IEEE Transactions on Aerospace and Electronic Systems*.

[37] Yang, L., Wang, R., Liang, J., Zhou, Y., Zhao, K., & Liu, X. (2022). Acknowledgment Mechanisms for Reliable File Transfer Over Highly Asymmetric Deep-Space Channels. *IEEE Aerospace and Electronic Systems Magazine*, *37*(9), 42-51.

[38] Zhou, Y., Wang, R., Yang, L., Liang, J., Burleigh, S. C., & Zhao, K. (2022). A Study of Transmission Overhead of a Hybrid Bundle Retransmission Approach for Deep-Space Communications. *IEEE Transactions on Aerospace and Electronic Systems*, *58*(5), 3824-3839.

[39] Fahad, M., Airf, H., Kumar, A., & Hussain, H. K. (2023). Securing Against APTs: Advancements in Detection and Mitigation. *BIN: Bulletin Of Informatics*, *1*(2).

[40] Kumar, A., Fahad, M., Arif, H., & Hussain, H. K. (2023). Navigating the Uncharted Waters: Exploring Challenges and Opportunities in Block chain-Enabled Cloud Computing for Future Research. *BULLET: Jurnal Multidisiplin Ilmu*, *2*(6), 1297-1305.

[41] Yang, L., Wang, R., Liu, X., Zhou, Y., Liang, J., & Zhao, K. (2021, July). An Experimental Analysis of Checkpoint Timer of Licklider Transmission Protocol for Deep-Space Communications. In *2021 IEEE 8th International Conference on Space Mission Challenges for Information Technology (SMC-IT)* (pp. 100-106). IEEE.

[42] Zhou, Y., Wang, R., Liu, X., Yang, L., Liang, J., & Zhao, K. (2021, July). Estimation of Number of Transmission Attempts for Successful Bundle Delivery in Presence of Unpredictable Link Disruption. In *2021 IEEE 8th International Conference on Space Mission Challenges for Information Technology (SMC-IT)* (pp. 93-99). IEEE.

[43] Liang, J. (2023). *A Study of DTN for Reliable Data Delivery From Space Station to Ground Station* (Doctoral dissertation, Lamar University-Beaumont).

[44] Tinggi, M., Jakpar, S., Chin, T. B., & Shaikh, J. M. (2011). Customers? Confidence and trust towards privacy policy: a conceptual research of hotel revenue management. *International Journal of Revenue Management*, *5*(4), 350-368.

[45] Alappatt, M., Sheikh, J. M., & Krishnan, A. (2010). Progress billing method of accounting for long-term construction contracts. *Journal of Modern Accounting and Auditing*, *6*(11), 41.

[46] Krishnan, A., Chan, K. M., Jayaprakash, J. C. M., Shaikh, J. M., & Isa, A. H. B. M. (2008). Measurement of performance at institutions of higher learning: the balanced score card approach. *International Journal*

of Managerial and Financial Accounting, *1*(2), 199-212.

[47] Al-Takhayneh, S. K., Karaki, W., Chang, B. L., & Shaikh, J. M. (2022). Teachers' psychological resistance to digital innovation in jordanian entrepreneurship and business schools: Moderation of teachers' psychology and attitude toward educational technologies. *Frontiers in Psychology*, *13*, 1004078.

[48] Mamun, M. A., & Shaikh, J. M. (2018). Reinventing strategic corporate social responsibility. *Journal of Economic & Management Perspectives*, *12*(2), 499-512.

[49] Mwansa, S., Shaikh, J., & Mubanga, P. (2020). Special economic zones: An evaluation of Lusaka south-multi facility economic zone. *Journal of Social and Political Sciences*, *3*(2).

[50] Rani, N. S. A., Hamit, N., Das, C. A., & Shaikh, J. M. (2011). Microfinance practices in Malaysia: from'kootu'concept to the replication of the Grameen Bank model. *Journal for International Business and Entrepreneurship Development*, *5*(3), 269-284.

[51] Yuan, X., Kaewsaeng-On, R., Jin, S., Anuar, M. M., Shaikh, J. M., & Mehmood, S. (2022). Time lagged investigation of entrepreneurship school innovation climate and students motivational outcomes: Moderating role of students' attitude toward technology. *Frontiers in Psychology*, *13*, 979562.

[52] Shamil, M. M. M., & Junaid, M. S. (2012). Determinants of corporate sustainability adoption in firms. In *2nd International Conference on Management. Langkawi, Malaysia*.

[53] Ali Ahmed, H. J., & Shaikh, J. M. (2008). Dividend policy choice: do earnings or investment opportunities matter?. *Afro-Asian Journal of Finance and Accounting*, *1*(2), 151-161.

[54] Odhigu, F. O., Yahya, A., Rani, N. S. A., & Shaikh, J. M. (2012). Investigation into the impacts of procurement systems on the performance of construction projects in East Malaysia. *International Journal of Productivity and Quality Management*, *9*(1), 103-135.

[55] Shaikh, J. M. (2010). Reviewing ABC for effective managerial and financial accounting decision making in corporate entities. In *Allied Academies International Conference. Academy of Accounting and Financial Studies. Proceedings* (Vol. 15, No. 1, p. 47). Jordan Whitney Enterprises, Inc.

[56] Ali Ahmed, H. J., Shaikh, J. M., & Isa, A. H. (2009). A comprehensive look at the re-examination of the re-evaluation effect of auditor switch and its determinants in Malaysia: a post crisis analysis from Bursa Malaysia. *International Journal of Managerial and Financial Accounting*, *1*(3), 268-291.

[57] Abdullah, A., Khadaroo, I., & Shaikh, J. (2017). XBRL benefits, challenges and adoption in the US and UK: Clarification of a future research agenda. In *World Sustainable Development Outlook 2007* (pp. 181-188). Routledge.

[58] Tinggi, M., Jakpar, S., Tiong, O. C., & Shaikh, J. M. (2014). Determinants on the choice of telecommunication providers among undergraduates of public universities. *International Journal of Business Information Systems*, *15*(1), 43-64.

[59] Jasmon, A., & Shaikh, J. M. (2004). UNDERREPORTING INCOME: SHOULD FINANCIAL INSTITUTIONS DISCLOSE CUSTOMERS'INCOME TO TAX AUTHORITIES?. *JOURNAL OF INTERNATIONAL TAXATION*, *15*(8), 36-43.

[60] Mwansa, S., Shaikh, J. M., & Mubanga, P. (2020). Investing in the Lusaka South Multi Facility Economic Zone. *Advances in Social Sciences Research Journal*, *7*(7), 974-990.

[61] Junaid, M. S., & Dinh Thi, B. L. (2017). Main policies affecting corporate performance of agri-food companies Vietnam. *Academy of Accounting and Financial Studies Journal*, *21*(2).

[62] Sheikh, M. J. (2015, November). Experiential learning in entrepreneurship education: A case Of CEFE methodology in Federal University of Technology Minna, Nigeria. Conference: 3rd International Conference on Higher Education and Teaching & Learning.

ISSN Online : 2709-5088
ISSN Print : 2709-507X
IJCST

[63] Chafjiri, M. B., & Mahmoudabadi, A. (2018). Developing a conceptual model for applying the principles of crisis management for risk reduction on electronic banking. *American Journal of Computer Science and Technology*, *1*(1), 31-38.

[64] Lynn, L. Y. H., Evans, J., Shaikh, J., & Sadique, M. S. (2014). Do Family-Controlled Malaysian Firms Create Wealth for Investors in the Context of Corporate Acquisitions. *Capital Market Review*, *22*(1&2), 1-26.

[65] Shamil, M. M. M., Shaikh, J. M., Ho, P. L., & Krishnan, A. (2012). The Relationship between Corporate Sustainability and Corporate Financial Performance: A Conceptual Review. In *Proceedings of USM-AUT International Conference 2012 Sustainable Economic Development: Policies and Strategies* (Vol. 167, p. 401). School of Social Sciences, Universiti Sains Malaysia.

[66] Chafjiri, M. B., & Mahmoudabadi, A. (2018). Developing a conceptual model for applying the principles of crisis management for risk reduction on electronic banking. *American Journal of Computer Science and Technology*, *1*(1), 31-38.

[67] Lynn, L. Y. H., & Shaikh, J. M. (2010). Market Value Impact of Capital Investment Announcements: Malaysia Case. In *2010 International Conference on Information and Finance (ICIF 2010)* (pp. 306-310). Institute of Electrical and Electronics Engineers, Inc..

[68] Shaikh, J. (2010). Risk Assessment: Strategic Planning and Challenges while Auditing. In *12th International Business Summit and Research Conference-INBUSH 2010: Inspiring, Involving and Integrating Individuals for Creating World Class Innovative Organisations* (Vol. 2, No. 2, pp. 10-27). Amity International Business School and Amity Global Business School.

[69] Shaikh, J. M. (2008). Hewlett-Packard Co.(HP) accounting for decision analysis: a case in International financial statement Analysis. *International Journal of Managerial and financial Accounting*, *1*(1), 75-96.

[70] Jasmon, A., & Shaikh, J. M. (2003). A PRACTITIONER'S GUIDE TO GROUP RELIEF. *JOURNAL OF INTERNATIONAL TAXATION*, *14*(1), 46-54.

[71] Kangwa, D., Mwale, J. T., & Shaikh, J. M. (2020). Co-Evolutionary Dynamics Of Financial Inclusion Of Generation Z In A Sub-Saharan Digital Financial Ecosystem. *Copernican Journal of Finance & Accounting*, *9*(4), 27-50.

[72] ZUBAIRU, U. M., SAKARIYAU, O. B., & JUNAID, M. S. (2015). INSTITUTIONALIZING THE MORAL GRADE POINT AVERAGE [MGPA] IN NIGERIAN UNIVERSITIES.

[73] Shaikh, J., & Evans, J. (2013). CORPORATE ACQUISITIONS OF MALAYSIAN FAMILYCONTROLLED FIRMS. *All rights reserved. No part of this publication may be reproduced, distributed, stored in a database or retrieval system, or transmitted, in any form or by any means, electronics, mechanical, graphic, recording or otherwise, without the prior written permission of Universiti Malaysia Sabah, except as permitted by Act 332, Malaysian Copyright Act of 1987. Permission of rights is subjected to royalty or honorarium payment.*, *7*, 474.

[74] Jasmon, A., & Shaikh, J. M. (2001). How to maximize group loss relief. *Int'l Tax Rev.*, *13*, 39.

[75] SHAMIL, M., SHAIKH, J., HO, P., & KRISHNAN, A. External Pressures. *Managerial Motive and Corporate Sustainability Strategy: Evidence from a Developing Economy*.

[76] Bhasin, M. L., & Shaikh, J. M. (2012). Corporate governance through an audit committee: an empirical study. *International Journal of Managerial and Financial Accounting*, *4*(4), 339-365.

[77] Ahmed, H. J. A., Lee, T. L., & Shaikh, J. M. (2011). An investigation on asset allocation and performance measurement for unit trust funds in Malaysia using multifactor model: a post crisis period analysis. *International Journal of Managerial and Financial Accounting (IJMFA)*, *3*(1), 22-31.

[78] Wang, Q., Azam, S., Murtza, M. H., Shaikh, J. M., & Rasheed, M. I. (2023). Social media addiction and employee sleep: implications for performance and wellbeing in the hospitality industry. *Kybernetes*.

[79] Jasmon, A., & Shaikh, J. M. (2003). Tax strategies to discourage thin capitalization. *Journal of International Taxation*, *14*(4), 36-44.

[80] Shaikh, J. M., & Mamun, M. A. (2021). Impact of Globalization Versus Annual Reporting: A Case. *American Journal of Computer Science and Technology*, *4*(3), 46-54.

[81] M. Shamil, M., M. Shaikh, J., Ho, P. L., & Krishnan, A. (2014). The influence of board characteristics on sustainability reporting: Empirical evidence from Sri Lankan firms. *Asian Review of Accounting*, *22*(2), 78-97.

[82] Shaikh, J. M., Islam, M. R., & Karim, A. M. Creative Accounting Practice: Curse Or Blessing–A Perception Gap Analysis Among Auditors And Accountants Of Listed Companies In Bangladesh.

[83] Shamil, M. M., Gooneratne, D. W., Gunathilaka, D., & Shaikh, J. M. (2023). The effect of board characteristics on tax aggressiveness: the case of listed entities in Sri Lanka. *Journal of Accounting in Emerging Economies*, (ahead-of-print).

[84] Shaikh, I. M., Alsharief, A., Amin, H., Noordin, K., & Shaikh, J. (2023). Inspiring academic confidence in university students: perceived digital experience as a source of self-efficacy. *On the Horizon: The International Journal of Learning Futures*, *31*(2), 110-122.

[85] Shaikh, J. M. (2023). Considering the Ethics of Accounting in Managing Business Accounts: A Review. *TESS Res Econ Bus*, *2*(1), 115.

[86] Naruddin, F., & Shaikh, J. M. (2022). The Effect of Stress on Organizational Commitment, Job Performance, and Audit Quality of Auditors in Brunei.

[87] Izzaty, D. N., Shaikh, J. M., & Talha, M. (2023). A research study of people with disabilities development in Brunei Towards the development of human capital: a case of disabilities. *International Journal of Applied Research in Management, Economics and Accounting*, *1*(1), 22-30.

[88] Tin Hla, D., Hassan, A., & Shaikh, J. (2013). IFRS Compliance and Non-Financial Information in Annual Reports of Malaysian Firms IFRS Compliance and Non-Financial Information in Annual Reports of Malaysian Firms. *The IUP journal of accounting research and audit*, *12*, 7-24.

[89] Yeo, T. S., Abdul Rani, N. S., & Shaikh, J. (2010). Impacts of SMEs Character in The Loan Approval Stage. In *Conference Proceeding*. Institute of Electrical and Electronics Engineers, Inc..

[90] Papa, M., Sensini, L., Kar, B., Pradhan, N. C., Farquad, M. A. H., Zhu, Y., ... & Mazı, F. Research Journal of Finance and Accounting.

[91] Shaikh, J. M., & Linh, D. T. B. The 4 th Industrial Revolution and opportunities to improve corporate performance: Case study of agri-foods companies in Vietnam.