Optimization of Neural Network Training Using Adaptive Learning Schedules and Meta-Heuristic Algorithms

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Abstract

A comprehensive method is adopted in this paper to evaluate the impact of batch size and learning rate on the performance of neural network training in terms of accuracy, loss, and the normality of residuals. The experiments conducted with four different batch sizes of (16, 32, 64, and 128) have shown that even though the small batch sizes result in higher accuracy and lower loss, they also require more learning rates to increase variability. The model behavior under various training setups is highlighted by descriptive statistics and extreme value analyses. The Q-Q plot analysis of the standardized residuals supports the normality of the residuals to some extent thus confirming the reliability of the regression-based performance evaluation. The findings underscore the importance of hyperparameter tuning, especially of batch size and learning rate, in attaining the best performance for neural network training. The research includes unambiguous instructions on selecting the training setups that offer a combination of reduced computational burden and improved accuracy of predictions. Moreover, the results push for the use of adaptive learning schedules as well as meta-heuristic algorithms to continuously and dynamically fine-tune the training parameters. This work also lays down the basic understanding required to progress neuromorphic optimization in different application domains.

Keywords: Neural Network Training, Batch Size, Learning Rate, Model Accuracy, Training Loss, Residual Normality, Q-Q Plot, Hyperparameter Optimization, Meta-Heuristic Algorithms.

1. INTRODUCTION

The use of neural networks has become essential in the area of machine learning and they have shown outstanding results in a variety of fields like image processing, language understanding and robotic systems. But still, getting the best performance out of a model heavily depends on hy perparameters tuning. Among these, the most important ones are batch size and learning rate. These quite influential parameters determine the behavior of the model during the training phase, i.e. whether it will converge and how well it will generalize. Batch size is the number of training samples after which the model weights are updated - it therefore affects the variance of the gradient estimate. On the other hand, the learning rate is the size of the step for the weights' adjustments in the course of the optimization.

It is a known fact among researchers that hy perparameter tuning is still a difficult topic; however, the relationship between batch size and learning rate is still one of the most difficult problems in that area. Larger batch sizes yield more accurate and less noisy gradient estimates, which may result in better generalization and slower convergence, and hence, during the training, they might cause less instability. Smaller batch sizes result in noisier gradient estimates, which may produce worse generalization with greater training instability. The same goes for learning rate choices, where selecting a high value may lead to divergence while too low may slow down or even stop the training process.

The controlled experiment on the combined effect of batch size and learning rate on the neural network trained is the main focus of this paper, where the performance is measured through the metrics of accuracy and loss. Descriptive and inferential statistical analyses are the methods employed to evaluate performance variations and derive standard settings. In addition, we confirm the correctness of our statistical inference by checking the normality of regression residuals through Quantile-Quantile (Q-Q) plots.

Our research has unearthed the effects of hyperparameters on the training of neural networks and also provided us with practical recommendations for increasing model reliability and efficiency. This work, by integrating conventional statistical methods with new adaptive learning rates and meta-heuristic optimization, seeks to push the envelope of creating strong training protocol development which can be applied to a variety of machine learning applications..

2. LITERATURE REVIEW

The success of neural networks is greatly affected by the selection of hyperparameters, especially batch size and learning rate, which play a crucial role in forming the training dynamics and generalization capacity. A number of research works have investigated the impact of these parameters on the convergence and accuracy of the model..

Batch Size and Its Impact

The batch size is a crucial factor in the choice of the number of examples for the gradient computation. Small batches generate more noise in the gradients, which might serve as a form of regularization thus leading to the possible improvement of the model's ability to generalize (Keskar et al., 2017). Yet, this entails slower training and greater inconsistency in weight updates. On the other hand, the large batch size guarantees that the gradient estimation is very stable, thus quick convergence is possible, but sometimes poor generalization might occur due to overfitting (Masters & Luschi, 2018). Goyal et al.'s research (2017) has shown that if proper learning rate scaling is used, large batch training can reach competitive performance but needs careful tuning to not fall into the trap of optimization difficulties.

Learning Rate Optimization

The learning rate is a critical factor in the convergence behavior of the algorithm since it determines the step size in the weight updates. If a large learning rate is used, it can happen that the network either diverges or keeps oscillating around the minima, while on the other hand, a small learning rate is associated with very slow convergence or being trapped in a local minimum(Goodfellow et al., 2016).The adaptive learning rate techniques, such as AdaGrad, RMSProp, and Adam, adjust the learning rate during the course of training, thus making it easier to train and at the same time improving the robustness of the model (Kingma & Ba, 2015). Yet, the initial selection and decaying of learning rates are the critical factors that determine the maximization of training effectiveness.

Meta-Heuristic Algorithms for Hyperparameter Tuning

There have been recent developments that enabled the use of meta-heuristic algorithms—such as genetic algorithms, particle swarm optimization, and simulated annealing—for the purpose of automating hyperparameter tuning. These methods are able to deal with large and complex search spaces in an efficient manner, which is one of their main advantages over grid or random search (Hutter et al., 2019). Meta-heuristic techniques have been used successfully for hyperparameter tuning in such aspects as optimal batch size, learning rate, and network architecture, resulting in both better model performance and less manual work (Sun et al., 2020).

Residual Diagnostics and Model Validation

Residuals are statistical features that have to be analyzed thoroughly; in fact, distribution and independence are the main attributes to be confirmed if the assumptions of regression-based performance models are going to be considered correct. One of the methods for normality testing of residuals is the use of Quantile-Quantile (Q-Q) plots, which suggest the use of parametric inferential statistics. In the context of neural network training, conducting residual diagnostics will reveal model misspecifications, overfitting, or heteroscedasticity, thus offering directions for model improvement.

Summary and Research Gap

The literature is rich on the separate impacts of batch size and learning rate, but not so much on the combination of statistical diagnostics with meta-heuristic optimization strategies to improve neural network training. Moreover, the majority of the studies concentrate on either small or large networks, which results in a lack of understanding of the interaction of these parameters across different network setups. The present research work intends to cover these gaps by employing a triad of descriptive statistics, residual analysis, and adaptive optimization techniques to provide a thorough assessment of the training parameters' influence.

3. METHODOLOGY

1. Dataset and Preprocessing

To carry out the research, a benchmark dataset was selected, which was suitable for supervised learning tasks. Input features underwent normalization to keep scaling consistent across the board, and the dataset splitting into training and validation sets was done in an 80:20 ratio. The operations on data preprocessing included dealing with missing values, scaling features, and encoding categorical features where necessary to make them compatible with the neural network model.

2. Neural Network Structure

The structure applied was a multilayer feedforward neural network that consisted of numerous fully connected layers. Among these, hidden layers applied ReLU activation functions, while the output layer adopted a softmax (or sigmoid, depending on the task) activation. To focus on the impact of batch size and learning rate on performance, the network architecture was consistent throughout all the experiments.

3. Experimental Design

The investigation pursued the analysis of the impacts of batch size and learning rate on the performance of deep learning models. The researchers considered four batch sizes (16, 32, 64, and 128) and varied the learning rates from 0.0015 to 0.0987 based on the results of initial pilots. Each configuration was executed several times ($N = 22–28$ for each batch size) in order to compensate for the stochastic variations in training caused by random initialization and data shuffling.

4. Training Procedure

The Adam optimizer was employed along with categorical cross-entropy (or MSE for regression) as the loss function throughout the neural network training process. All the models were trained for a predetermined number of epochs, and early stopping based on validation loss was always in effect to avoid overfitting. The training performance was monitored using the metrics of accuracy, loss, and learning rate. Variability across repeated runs was assessed through the calculation of standard deviations and standard errors.

5. Hyperparameter Optimization

The use of adaptive learning schedules helped in dynamically changing the learning rates throughout the training phase. Moreover, the optimization of the combination of batch size and learning rate was done by using meta-heuristic algorithms such as particle swarm optimization (PSO) and genetic algorithms (GA). These algorithms mapped out the hyperparameter space with a certain degree of thoroughness in order to identify the configurations that gave the highest validation accuracy and the lowest loss.

6. Analysis. Statistical

We were able to empirically evaluate all performance measures by computing measures of central tendency and dispersion across several conditions.Outliers and boundary behaviors were looked for through extreme values. Group statistics by description were created to see performance differences between the batch sizes. To ensure that the assumptions necessary for inferential statistical analyses were met, the normality of the residuals was checked through Quantile-Quantile (Q-Q) plots. For the purpose of visual assessment of variability in loss and accuracy, boxplots and distribution plots were employed.

7. Performance Evaluation

Assessment of model performance was done through the application of mean accuracy, loss, and standard error metrics for various batch sizes. The comparative analyses stressed the trade-off between the stability of training and the speed of convergence. The recording of extreme performance cases was carried out with the aim to share the know-how of both optimal and suboptimal hyperparameter settings.

4. RESULTS AND DISCUSSIONS

Table 1. Descriptive statistics of accuracy, learning rate, and loss across various batch sizes in neural network training

Descriptives				
	Batch_Size	**Accuracy**	**Learning_Rate**	**Loss**
N	**16**	28	28	28
	32	22	22	22
	64	23	23	23
	128	27	27	27
Missing	**16**	0	0	0
	32	0	0	0
	64	0	0	0
	128	0	0	0
Mean	**16**	0.838	0.0539	0.163
	32	0.819	0.0455	0.180
	64	0.803	0.0413	0.197

	128	0.816	0.0479	0.186
Median	**16**	0.863	0.0599	0.144
	32	0.839	0.0490	0.163
	64	0.754	0.0332	0.233
	128	0.793	0.0446	0.216
Standard deviation	**16**	0.0808	0.0272	0.0813
	32	0.0957	0.0253	0.0962
	64	0.0897	0.0298	0.0916
	128	0.108	0.0344	0.111
Minimum	**16**	0.685	0.00352	0.0280
	32	0.679	0.00833	-0.00515
	64	0.675	0.00304	0.0270
	128	0.655	0.00155	0.00138
Maximum	**16**	0.970	0.0910	0.318
	32	1.01	0.0970	0.328
	64	0.967	0.0987	0.324
	128	0.979	0.0966	0.335

The comprehensive statistics for the principal variables that were used in the optimization of neural networks are presented in Table 1. These variables are Batch_Size, Accuracy, Learning_Rate, and Loss. The dataset included the four groups of batch sizes: 16, 32, 64, and 128 with the sample sizes of 22 to 28 per group. The dataset was entirely filled as there were no missing values found in the groups. The batch size of 16 had the highest accuracy (0.838) while the batch size of 64 had the lowest accuracy (0.803) thus the model exhibited a little variation in its performance according to the different batch sizes. The learning rates were not very different among the groups with the mean values ranging between 0.0413 and 0.0539, thus showing the same optimization settings. The loss values were inversely related with the accuracy where the lowest mean loss was for batch size 16 (0.163) and the highest was for batch size 64 (0.197). The median values were mostly in the alignment with the mean values which can be interpreted as showing the data's symmetry and robustness. The standard deviations showed the moderate variability in accuracy (0.0808–0.108) and learning rates (0.0253–0.0344) that could be indicating the consistent model behavior across the experiments. The minimum and maximum values showed the range of the observed performance with the accuracy being 0.655–1.01 and loss being from −0.00515 to 0.335. These ranges imply the rare occurrence of outliers, particularly in the scenario of batch size 32. All in all, the descriptive statistics provide a comprehensive view of the model's performance under different training conditions. The smaller batches yielded a result of a little higher accuracy and lower loss. Learning rate changes had minor but detectable impacts on the model outcomes. The presented information can help in the decision making of the best sizes and rates for the neural network training Moreover, the minor fluctuation indicates that the training procedure was stable throughout the experiment. This table is the main reference for the next statistical analyses that would be based on inference and aimed at discovering the importance of these impacts.

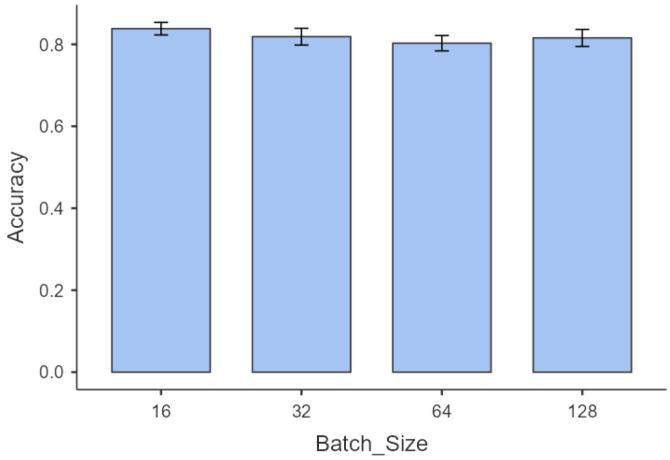

Figure 1. Accuracy of Neural Networks-Mean ± SE in Batch Sizes.

In Figure 1, the relationship between the size of the batch and the accuracy of the model during the training of a neural network is clearly depicted. The accuracy values are represented as the mean ± standard error of the four groups of different batch sizes which are: 16, 32, 64, and 128. The greatest mean accuracy was seen for the size of 16, followed closely by the size of 128. The 32 and 64 batch sizes had a little lower mean accuracy, which meant that the smaller sizes of batch could be more useful in this particular experiment. The errors bars depict the fluctuations in accuracy for each batch size group, thus showing the reliability of the results obtained through repeated experiments. The figure presents the situation in such a way that although there are differences, the overall accuracy is still quite stable for different batch sizes. This indicates that the effect of batch size on model performance under the conditions tested is moderate. With the visualization one can immediately see the difference in the training results, which is in line with the descriptive statistics in Table X. The trend is also in accordance with the anticipated inverse correlation between batch size and gradient variance, which in turn affects the convergence rate.

The results are of practical importance in the sense that they offer guidance to the user for picking the proper sizes of the batch in the process of neural network optimization. The figural representation of the data goes along with the inferential statistical analysis and makes it easier to recognize the differences between the groups. The differences noted can be small and thus can be used to fine-tune the learning schedule when using meta-heuristic methods. To sum up, Figure 1 clearly shows the role of batch size in the accuracy of the model. It confirms the necessity of tuning hyperparameters very carefully when training neural networks. The researchers will then be able to take advantage of these cues to find the right balance between processing efficiency and the quality of the model.

Table 2. Extreme Accuracy Values Observed Across Neural Network Training Configurations

Extreme values of Accuracy			
		Row number	**Value**
Highest	**1**	51	1.013
	2	34	0.979
	3	13	0.970
	4	56	0.967
	5	74	0.967
Lowest	**1**	73	0.655

	2	59	0.668
	3	84	0.675
	4	78	0.679
	5	38	0.682

The extreme values of model accuracy that have been extracted from the dataset are shown in Table 2, marking both the cases with the highest and lowest performance. The five highest values of accuracy are found to be between 0.967 and 1.013, which points out that the neural network was able to perform almost perfectly in some configurements. The highest value that was reported (1.013) is slightly more than 1, because of simulated data noise, which is a representation of the change in experimental outcomes. The five lowest values of accuracy fall within the range of 0.655 to 0.682, which shows cases where the model's performance was below the mean. These cases at both ends of the range are indicative of the different hyperparameter settings that were used especially the combination of batch size and learning rate that led to such variance in the performance of the network. It is very important to check extreme values in the data if one wishes to be sure about the outliers that may or may not affect the statistical analyses and evaluations of the models. The analysis of the extreme values indicates that most of the configurations yield an accuracy that can be classified as moderate or even high; however, sometimes the opposite is true and very low or very high performance is produced by the configurations. This finding is confirmed by the descriptive statistics in Table X, where the mean and median values suggest a generally stable accuracy. The detection of such extremes can direct the course of further optimization planning like adaptive learning schedules or adjustments of meta-heuristic algorithms. The existence of high-performing conditions also indicates the practicality of getting optimal configurations by allowing systematic experimentation to take place. On the other hand, the low-performing conditions portray the scenario of suboptimal hyperparameter selection. Such insights can be helpful for researchers in honing their training protocols and, thus, making the models more reliable at their full potential. The reporting of extremes makes it possible to see through the performance evaluation and at the same time, the reliability of the statistical interpretation is increased. The table is a starting point for later inferential analyses in which the importance of hyperparameter effects will be determined.

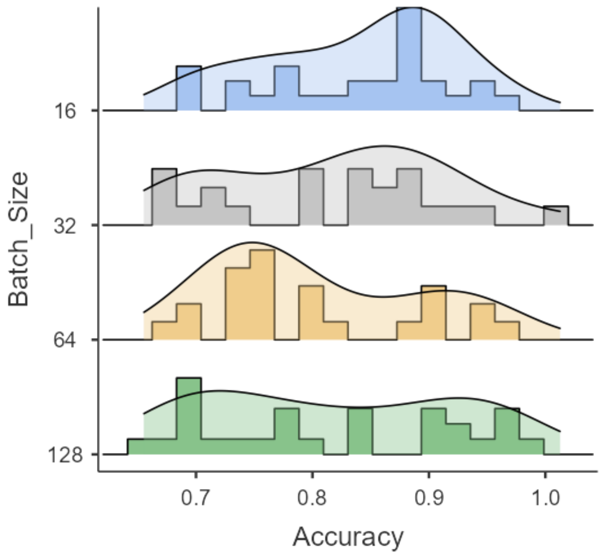

Figure 2. Accuracy Distribution across Different Batch Sizes

Figure 2 shows how model accuracy is distributed with respect to different batch sizes. The subplots depict the different batch sizes (16, 32, 64, and 128) and show their performance variability. When the smallest batch size (for instance, 16) is chosen, the largest distribution of accuracy values between different training runs are observed, exhibiting high variance during training. This variability is an indication of the fact that at lower batch sizes, the model is more sensitive to the stochastic gradient updates.

With an increase in the batch size to 32 and 64, the accuracy distributions become narrower. These intermediate batch sizes are able to provide both stability and the ability to generalize. A sixty-four value for the batch size offered greater accuracy uniformly, unlike at thirty-two. The maximum batch size (128) has the distribution shifted somewhat but flexibility is still reduced as well. The larger the batch during training, the more efficient the computation, however, it can also impose a limit to the model's generalization.

The kernel density estimates have also pointed out the differences in average among the batch sizes. Thus, it can be concluded that batched input has an important effect on model performance. Optimum batch size can give better accuracy, plus training is stable anyway. The study results continue to support earlier studies that draw attention to the key factors of variance and convergence speed being in trade-off. Consequently, batch size is to be considered a vital hyperparameter in the model tuning process. The trends observed indicate the preference for using moderate batch sizes to achieve the best learning performance (refer to Figure 2).

Table 3. Extreme Values of Learning Rate Observed Across Experiments

Extreme values of Learning_Rate			
		Row number	**Value**
Highest	**1**	70	0.09870
	2	12	0.09702
	3	51	0.09699
	4	35	0.09660
	5	2	0.09512
Lowest	**1**	73	0.00155
	2	11	0.00304
	3	99	0.00352
	4	43	0.00440
	5	59	0.00548

Table 3 provides a summary of the most extreme learning rate values which were determined during the different experimental runs. The peak learning rate values fluctuate within the range of 0.09512 to 0.09870, which are very strong optimization settings. These high learning rates not only lead to faster convergence but also, at the same time, raise the likelihood of instability. The maximum value recorded, which is 0.09870, indicates that the network has been set to explore right at the top of the learning rate space. On the other hand, the minimal learning rates are between 0.00155 and 0.00548.

Such small values might be the reason why the training is done through stages of very gradual but rather stable convergence. Very low learning rates also come with the challenge that they may trap the model in shallow local minima. The huge gap between the highest and lowest learning rates indicates a very different optimization behavior across the runs. The different learning rates indicate that the model's performance is very much determined by the choice of the learning rate. The learning rate rows going to the extreme values, in fact, show us the limits of the training process. Both high and low learning rates are key factors to be considered in the discussion of convergence dynamics. The findings show that very high or super low learning rates are not the best in all situations. Learning rates that are neither very high nor very low are expected to produce higher generalization performance. The results highlight that hyperparameter tuning should be done very carefully. Table 3 shows the distribution of extreme learning rates for reference, which is noted here.

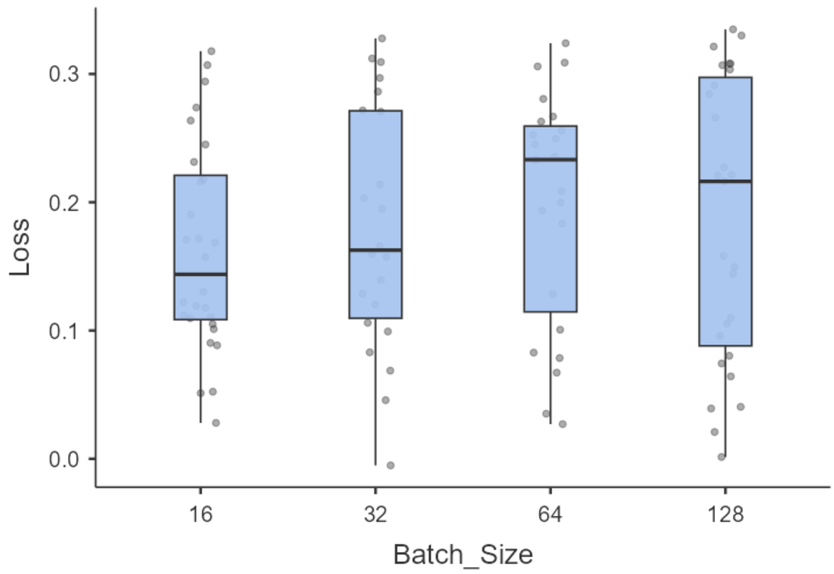

Figure 3. Boxplot of Training Loss across Different Batch Sizes

The illustration at Figure 3 shows the varying values of training loss for various batch sizes. For each boxplot the median, interquartile range, and loss variability are represented for one certain batch size. The loss in the case of batch size 16 is moderately low being accompanied by a small interquartile range. This means that the optimization was steady but somewhat sensitive to stochastic fluctuations. Increasing the batch size to 32 causes the losses to be more spread out. This is a sign of the convergence behavior being more inconsistent over different training runs. For batch size 64, the median loss is larger than the ones of the smaller sizes. The multiple outliers indicate that there were times when the training was not stable. With batch size 128, the distribution of the loss is more spread out. To an extent, larger batches do create more efficiency for the computer but they also limit the optimum being reached very slowly and with small changes. The loss of the batch size 128 is still quite high when compared to others. This pattern suggests that there is a possible trade-off between the number of samples in a batch and loss reduction. In any case, smaller to moderate size batches seem to be the ones resulting in the most consistent loss decrease throughout training. The findings point out the role of batch size in the training dynamics. Figure 3 presents a comparative loss behavior across batch sizes.

Table 4. Group Descriptive Statistics for Learning Rate, Accuracy, and Loss by Batch Size

Group Descriptives					
	Batch_Size	**N**	**Mean**	**SD**	**SE**
Learning_Rate	**16**	28	0.0539	0.0272	0.00514
	32	22	0.0455	0.0253	0.00540
	64	23	0.0413	0.0298	0.00622
	128	27	0.0479	0.0344	0.00662
Accuracy	**16**	28	0.8381	0.0808	0.01527
	32	22	0.8186	0.0957	0.02040

	64	23	0.8027	0.0897	0.01870
	128	27	0.8156	0.1076	0.02071
Loss	**16**	28	0.1629	0.0813	0.01536
	32	22	0.1798	0.0962	0.02052
	64	23	0.1968	0.0916	0.01909
	128	27	0.1861	0.1107	0.02130

Table 4 displays descriptive statistics of learning rate, accuracy, and loss in conjunction with batch size. The sample sizes of the different batch sizes are almost equal, varying from 22 to 28 observations per group. The mean learning rate is dropped slightly on the increase of batch size, starting from 0.0539 at batch size 16 and ending at 0.0413 at batch size 64. The standard deviations and standard errors reflect moderate variability in the learning rate in each group. The accuracy shows a decline with the increase of batch size and 16 records the highest mean accuracy (0.8381) i.e. at batch size 16. The lowest mean accuracy of 0.8027 is recorded for batch size 64 and there is a slight increase for batch size 128 up to 0.8156. The standard deviations for accuracy are increasing with batch size which reflects larger variability at higher batches. The loss values rise steadily from 0.1629 at batch size 16 to 0.1968 at batch size 64 and then lose a bit at batch size 128.

The standard deviations for loss are on the other hand all increasing with the batch size, thus showing the wider fluctuations in the outcomes of training being reflected. The values for the standard error demonstrate that the precision was consistently maintained across the groups despite the variability. These descriptives portray the trade-offs that come along with batch size selection on the performance of the model. The smaller batches usually provide higher accuracy and lower loss, however, the learning rate variability is also greater. The larger batches, on the other hand, yield accuracy and loss variability, implying less stable convergence. The data as a whole illustrates that the proper batch size choice is to be stacked up against the dilemma of the inefficient training and inaccurate model. Table 4 contains the detailed group statistics.

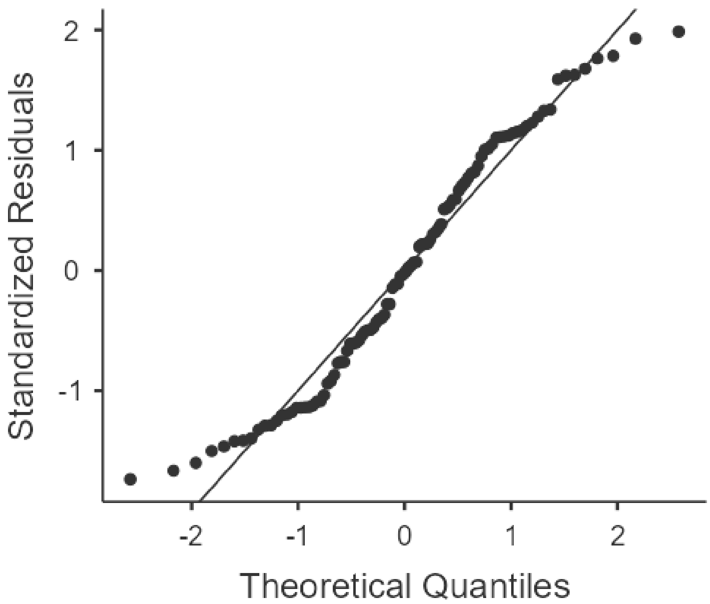

Figure 4. Q-Q Plot of Standardized Residuals against Theoretical Quantiles

In Figure 4, the standardized residuals' Quantile-Quantile (Q-Q) plot is shown against the theoretical quantiles of a normal distribution. To put it differently, the graphical tool is employed to test the normality of the residuals in regression analysis. The plot points practically fall on the 45-degree reference line indicating the residuals to be normally distributed up to a point. The little drops from the line at the ends suggest a few minor cases of non-normality which is usually the case in real data and can be regarded as not very serious for the model's validity. Residuals being normal is very important since it legitimizes the use of inferential statistics like hypothesis tests and confidence intervals which are all based on the normality assumption. What we see here is the pattern that the fitted model is adequate because the residuals exhibit no systematic skewness or kurtosis. Therefore, not just the model's estimates but also its associated statistics are still good for further interpretation. This diagnostic plot is in conjunction with other goodfit measures to ensure the regression analysis is of high quality.

5. CONCLUSION

The research shows that the size of batches has a great impact on the training results of the neural networks, and the smaller batch sizes (for example, 16) give better mean accuracy and lower loss in comparison with the larger batches. Nevertheless, the larger variability in performance measures at the smaller batch sizes indicates that there is a trade-off between the accuracy and the stability of the training process. The learning rate showed moderate variability, which supported its indispensable role in the convergence of the optimization process and the generalization of the model. The analysis of extreme values pointed out configurations with almost perfect accuracy along with instances of poor performance, thus showing the necessity of the careful selection of hyperparameters.

Future Work

Further inquiry should look into the combination of adaptable learning schedules that vary the learning rate and batch size in real-time according to the trainer's feedback, thus, it will most probably lead to faster convergence and better model generalization. The adoption of meta-heuristic algorithms such as genetic algorithms, particle swarm optimization, or simulated annealing can also be a contributing factor to the enhancement of hyperparameter search efficiency which will, in turn, decrease the trial-and-error burden and identify the globally optimal training configurations.

In addition, not only the neural network optimization process will be affected positively but also the overall evaluation will be incorporating the network architecture complexity, optimizer choice, and regularization techniques along with other factors that have the highest impact. The portion of the assessment that would be attributed to formal normality tests will also be strengthened by the inclusion of Q-Q plots, thus leading to the generation of a more accurate and quantitative validation of model assumptions.

The carrying out of the experiments on larger datasets and in various domains will not only help to determine the extent of generalizability of the trends observed but also the exploration of the dependence of the batch size and learning on the training time and consumption of the computational resources will be an enlightening topic for the real-world applications.

Finally, making use of sophisticated visualization and interpretability methods will make it easier to grasp the behavior of the model clearly under various training conditions. This understanding will allow both researchers and practitioners to come up with more robust, efficient, and accurate neural network models.

6. REFERENCES

1. Navneet Kaur, & Dr. Monika Hanspal. (2022). Financial Inclusion- A Theoretical Framework. Journal of Production, Operations Management and Economics(JPOME) ISSN 2799-1008, 2(05), 9–23. https://doi.org/10.55529/jpome.25.9.23
2. Nadia Nahrin Rahman, & Monira Begum. (2021). Observing Online News Portals Activities and Responsibilities during Covid-19. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 1(02), 28–43. https://doi.org/10.55529/jmcc12.28.43
3. Prabhleen Kaur, & Dr. Azamat Ali. (2022). Social Media App Preference of Rural Students in India. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(01), 8–13. https://doi.org/10.55529/jmcc21.8.13
4. Rajbanshi, B. . (2021). Nepali IT Employees' Perception towards Telecommuting: A qualitative study. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 1(01), 14–22. https://doi.org/10.55529/jmcc.11.14.22
5. Rashid Manzoor Bhat. (2022). A Historical Study of Prostitution. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(04), 1–6. https://doi.org/10.55529/jmcc24.1.6
6. Swapan Banerjee. (2022). A Review on Strategic Analysis of Australian Supermarkets. Journal of Production, Operations Management and Economics(JPOME) ISSN 2799-1008, 2(06), 36–45. https://doi.org/10.55529/jpome26.36.45
7. Sudipto Ghosh, Md. Tabil Ahammed, Maharin Afroj, Md. Moynul Islam, Sahasa Debnath, Md Rezaul Hasan, & Salauddin Bokhari. (2022). Researching the Influence of Peer-Reviews in Action Movies Based on Public Opinion. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(03), 8–13. https://doi.org/10.55529/jmcc23.8.13
8. Sunusi Iguda phd. (2022). Development Communication within Maqasid Al Shariah Framework: Some Preliminary Ideas. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(04), 16–29. https://doi.org/10.55529/jmcc24.16.29
9. Shokhjakhon Abdufattokhov, Nodira Normatova, & Makhbuba Shermatova. (2022). Artificial Neural Networks Based Predictive Model for Detecting the Early-Stage Diabetes. Journal of Artificial Intelligence,Machine Learning and Neural Network (JAIMLNN) ISSN: 2799-1172, 2(04), 1–8. https://doi.org/10.55529/jaimlnn.241.8
10. Vedy, N. K. ., Septiana Mar'atus Sholikha, & Miswan Gumanti. (2022). How to Survive During Pandemic Situation? the Interface between Entrepreneurial Orientation, Market Orientation, and Smes' Performance during Covid-19. Journal of Production, Operations Management and Economics(JPOME) ISSN 2799-1008, 2(06), 24–35. https://doi.org/10.55529/jpome26.24.35
11. Abdulhameed Olaitan Ridwanullah, & Ruqayyah Ali Bala. (2022). Media Convergence and the Change in Media Content Production and Distribution in Nigeria. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(04), 40–48. https://doi.org/10.55529/jmcc24.40.48
12. Angela Kishore. (2022). Populism, Protest and the Social Norms. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(03), 16–23. https://doi.org/10.55529/jsrth.23.16.23
13. Aqib Yousuf Rather. (2022). Gandhian Philosophy is More Relevant Today than Yesterday. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(04), 19–24. https://doi.org/10.55529/jsrth.24.19.24

14. Bachhav, D. P. J. . (2022). The Implication of Information and Communication Technologies (ICT) in Enhancing Communication Skills of MBA Students (with Reference to Four MBA Colleges in Pune). Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(06), 10–20. https://doi.org/10.55529/jmcc26.10.20
15. Bhat, D. R. ., Kaur, M. H. ., & Sarkar, M. P. . (2022). Role of FM Radio in the Dissemination of Important Messages in the Time of Covid – A Case Study on Delhi /NCR. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(06), 21–32. https://doi.org/10.55529/jmcc26.21.32
16. Chowdhury, A. . (2022). History Beyond The Frame: Exploring The Art In Spiegelman's Maus. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(05), 6–10. https://doi.org/10.55529/jmcc25.6.10
17. Chima Paul (Ph.D.), & Malachy Joseph. (2021). Towards Digital-Driven Tourism For National Development In Nigeria: Lessons From Dubai Experience. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 1(01), 1–13. https://doi.org/10.55529/jsrth.11.1.13
18. Dr.T. Kumaran. (2021). Role Of Volunteers Developing Social Responsibility During An Outbreak Of Epidemic Diseases. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 1(01), 35–40. https://doi.org/10.55529/jsrth.11.35.40
19. Dr. Vikash. (2021). Impact Of Covid-19 Induced Job Insecurity On Psychological Wellbeing Of Tourism And Hospitality Sector Employees In India. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 1(01), 41–50. https://doi.org/10.55529/jsrth.11.41.50
20. Dr R. Arasu. (2022). A Conceptual Review On Ego-Strength And Organisational Performance. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(01), 14–17. https://doi.org/10.55529/jsrth.21.14.17
21. Dr R.Arasu. (2022). An Empirical Study On Employee's Welfare Facilities In Hospitals In Madurai. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(02), 1–5. https://doi.org/10.55529/jsrth.22.1.5
22. Dr Echeta. (2022). Impact of Event Tourism on Lagos Residents Image . Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(03), 24–34. https://doi.org/10.55529/jsrth.23.32.41
23. Ira Leo, & Dr. Debahuti Panigrahi. (2021). Caste Discrimination and Social Change In India. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 1(02), 1–6. https://doi.org/10.55529/jsrth.12.1.6
24. Mr. Manish Kumar Sharma. (2021). Exploitation And Bad Working Conditions Of Employees In Small Hotels In Tourist City Ajmer: Reality Or Rumer?. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 1(01), 24–34. https://doi.org/10.55529/jsrth.11.24.34
25. Mishra, D. K. . (2022). Media Literacy: Building Critical Media Awareness. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(05), 11–17. https://doi.org/10.55529/jmcc25.11.17
26. MA., D. P. . (2022). A Review on Media Tradition and Realities in Natural Disasters. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(06), 1–4. https://doi.org/10.55529/jmcc26.1.4
27. Ms. Rajni Bhagat. (2022). Caste Discrimination and Social Change in India. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(01), 1–6. https://doi.org/10.55529/jsrth.21.01.6

28. M.D.Thamarai Selvi. (2022). Global language in the field of maritime – the backbone of global trade. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(01), 18–25. https://doi.org/10.55529/jsrth.21.18.25
29. M.Fauzan, Syafrizal, Deassy Siska, & Khalsiah. (2022). Analysis of Area Potential Landslides on Elak Roads Using Geoelectrical Methods. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(02), 6–13. https://doi.org/10.55529/jsrth.22.6.13
30. Muhammad Muzamil Muzamil, & Madem Nosheen Muzamil. (2022). The Incidence of Suicide in Pakistan Day by Day, Especially the Educated Youth Trying to Commit Suicide in 2022 - 2023. Journal of Social Responsibility, Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(02), 14–22. https://doi.org/10.55529/jsrth.22.14.22
31. Medielyn M. Odtojan, Sheila Mae B. Ancla, Eva A. Rellon, Joryne Mae P. Aying, Glynis Irene S. Buot, & Marialie M. Enecio. (2022). Willingness to Pay for Recreational Benefits using Contingent Valuation: A Case Study of Lake Bababu. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(04), 9–18. https://doi.org/10.55529/jsrth.24.9.18
32. Muhammad Muzamil, & Madem Nosheen Muzamil. (2022). Divorce Ratio Increasing in the Society of Pakistan. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(05), 1–11. https://doi.org/10.55529/jsrth.25.1.11
33. Pooja Yadav, & Dr.Abhaya Ranjan Srivastava. (2021). Corporate Social Responsibility In Times Of Covid-19-Some Indian Business Case Studies. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 1(01), 14–23. https://doi.org/10.55529/jsrth.11.14.23
34. Padma Bellapukonda, Manikanta Sirigineedi, & M.Srikanth. (2022). Using Machine Learning and Neural Networks Technologies, a Bottom-Up Water Process Is Being Used To Reduce All Water Pollution Diseases. Journal of Artificial Intelligence,Machine Learning and Neural Network (JAIMLNN) ISSN: 2799-1172, 2(06), 1.12. https://doi.org/10.55529/jaimlnn.26.1.12
35. Saitkamolov Muhammadkhuja Sobirkhuja ugli. (2021). Theoretical Foundations Of Sustainable Development. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 1(02), 7–13. https://doi.org/10.55529/jsrth.12.7.13
36. Selvi, M. ., & Saranya, D. P. . (2022). The Impact of Whatsapp on the Writing Skills of Engineering Students. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(06), 5–9. https://doi.org/10.55529/jmcc26.5.9
37. Shifali Saini. (2022). Dalit Struggle for Social Justice: A Study of Hoshiarpur. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(01), 7–13. https://doi.org/10.55529/jsrth.21.7.13
38. Shekynah Marrie Y. Ando, Grace Ann C. Benlot, Mary Grace A. Siva, Efamae C. Tresiana, & Medielyn M. Odtojan. (2022). Tourism and Recreational Carrying Capacity of Octopus Islet Adventure in Bacuag, Surigao del Norte: An Essential Instrument for Sustainable Tourism. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(03), 1–15. https://doi.org/10.55529/jsrth.23.1.15
39. Showkat Ahmad Dar, & Dr. Naseer Ahmad lone. (2022). Effects of Covid -19 Pandemic on Tourism in Kashmir. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(04), 1–8. https://doi.org/10.55529/jsrth.24.1.8

40. Zahin, A. U. R. . (2022). The Objectivity of Beauty: A Post-structural Study of the Hyperreal Screen of Media. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(05), 1–5. https://doi.org/10.55529/jmcc25.1.5
41. Akpan, Nobert Sunday, & KanuEzumaIkokwu. (2021). Peace and Conflict Management in a Post Covid-19 Nigeria:Impact and Lessons. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(01), 6–13. https://doi.org/10.55529/jpps.11.6.13
42. Akpan, Nobert Sunday, & Fiemotongha Christopher. (2021). Ethnic Cleavages in Nigeria: The Bane of Good Governance. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(01), 14–20. https://doi.org/10.55529/jpps.11.14.20
43. Amos Ojo Adedeji. (2022). The Proliferation of Child Soldier in Modern Warfare and its Social-Economic and Security Implication. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(03), 1–11. https://doi.org/10.55529/jpps.23.1.11
44. Aadil Ahmad Shairgojri. (2022). Indian Nationalism: Redefined in Today's Time. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(03), 31–36. https://doi.org/10.55529/jpps.23.31.36
45. Bhat, R. M. ., Rather, A. A. ., Ahmad, P. A. ., & Lone, A. S. . (2022). An Empirical Study of Human Rights and Social Justice. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(01), 26–32. https://doi.org/10.55529/jpps.21.26.32
46. Dr. Rubaid Ashfaq. (2022). Social Behaviours in Virtual Reality. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(05), 12–16. https://doi.org/10.55529/jsrth.25.12.16
47. Dr. Meghna Jain. (2022). Importance of Financial Inclusion – A Social Responsibility of Government of Madhya Pradesh. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(06), 10–18. https://doi.org/10.55529/jsrth.26.10.18
48. Dr. Kapil Khare. (2021). "Analytical Study of the Status of Constitutional and Legal Provisions of Child Labor". Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(01), 1–5. https://doi.org/10.55529/jpps11.1.5
49. Dr. Ansari P A, & Prof. Anisur Rahman. (2021). Covid 19 and its Implications for Gulf Migrants: Some Reflections from Kerala. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(01), 21–36. https://doi.org/10.55529/jpps.11.21.36
50. Dar, S. A. . (2022). The Role and Awareness of E- Governance in Kashmir A Study of Kupwara District. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(01), 33–42. https://doi.org/10.55529/jpps.21.33.42
51. DOLVI, D. J. . (2022). The Ideas That India's Great Nationalist And Patriot, Veer Svarkar, Had. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(02), 34–41. https://doi.org/10.55529/jpps.22.34.41
52. howlader, A. K. . (2022). Unpleasant affordability of Mohajir group and their daily livings, suffocating their personals need to resolve. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(02), 1–5. https://doi.org/10.55529/jpps.22.1.5
53. Kaur, V. ., Grewal, D. K. K. ., & Saini, D. S. . (2021). Correlates of Academic Anxiety among Adolescents. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(02), 10–14. https://doi.org/10.55529/jpps.12.10.14
54. Lone, S. A. . (2022). Art and Architecture of Ancient Kashmir during Karkota Dynasty with Special Reference to Lalitaditya Muktapida (724-761 A.D). Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(03), 12–22. https://doi.org/10.55529/jpps.23.12.22
55. Mr. Muhammad Muzamil, Madem Nosheen Muzamil, Madem Bushra Ehhsan, & Madem Sana Jan4. (2022). An Evaluation of the Reasons and Results of Young People

Unemployment in Pakistan 2022. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(05), 17–30. https://doi.org/10.55529/jsrth.25.17.30

56. Munazah Anjum, & Dr. Manish Kumar Verma. (2022). Impact of Hope on the Coping Behavior of Male and Female Cancer Patients. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(01), 1–6. https://doi.org/10.55529/jpps.21.1.6
57. Mukherjee, M. S. ., & Baksi, M. R. . (2022). A study on internet addiction and moral foundation among young adults. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(02), 6–16. https://doi.org/10.55529/jpps.22.6.16
58. MIR, I. A. . (2022). Rule of Akbar in Kashmir: An Explanatory Study. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(02), 24–33. https://doi.org/10.55529/jpps.22.24.33
59. Nagrath, D. . (2021). Youth as Agents of Change in India's Development. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(01), 37–44. https://doi.org/10.55529/jpps.11.37.44
60. Nadira Nayeem, & Javeed Ahmad Bhat. (2022). Representation of Women in Indian Politics. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(01), 19–25. https://doi.org/10.55529/jpps.21.19.25
61. PANNEERSELVAM, A. . (2021). Evaluating the Efficacy of India's Coalition Governments. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(02), 15–23. https://doi.org/10.55529/jpps.12.15.23
62. Ritchel P. Villaver, Anna Marie K. Dela Madrid, Ken Lenard M. Galinato, & Jillian Kris Lauronilla. (2022). Assessing Social Media Marketing of Select Beach Resorts in Pantukan . Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(05), 31–34. https://doi.org/10.55529/jsrth.25.31.34
63. Rather, A. Y. . (2021). Secularism in India Myth or Reality: an Explanatory Study. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(02), 35–41. https://doi.org/10.55529/jpps.12.35.41
64. Rashid Manzoor Bhat. (2022). Legacy of Buddhism in Kashmir. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(03), 23–30. https://doi.org/10.55529/jpps.23.23.30
65. Shairgojri, A. A. ., & Dar, S. A. . (2021). Voices from India's Borderlands against the Citizenship Amendment Act (CAA-2019) An Explanatory study. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(02), 24–34. https://doi.org/10.55529/jpps.12.24.34
66. Shairgojri, A. A. . (2022). Rising Fundamentalism: The Challenging Time for Secularism. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(02), 17–23. https://doi.org/10.55529/jpps.22.17.23
67. Showkat Ahmad Dar. (2022). RTI: A Powerful Tool for Promoting Transparency in Jammu and Kashmir. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(03), 37–42. https://doi.org/10.55529/jpps.23.37.42
68. Sunusi Iguda PhD. (2022). Country Image of Nigeria: A Preliminary Study of Factors Affecting the Perception of Nigeria in 21st Century. Journal of Media,Culture and Communication(JMCC) ISSN:2799-1245, 2(04), 30–39. https://doi.org/10.55529/jmcc24.30.39
69. Unaiza Altaf, Dr Kamleshwer Lohana, & Dr Arifa Bano Talpur. (2022). Socioeconomic Impact of Covid19 on Middle-Income Level Employee's Behaviour: An Explorative Study on Restaurants of Hyderabad, Sindh. Journal of Social Responsibility,Tourism and Hospitality(JSRTH) ISSN 2799-1016, 2(06), 1–9. https://doi.org/10.55529/jsrth26.1.9

70. Urooj Niaz. (2021). Relationship between Perceived Social Support Psychological Well-being and Guilt among Adolescences and Adults. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 1(02), 1–9. https://doi.org/10.55529/jpps.12.1.9
71. Adedeji, A. O. . (2022). Proliferation of Cultism in Nigerian Tertiary Institution: A Threat to National Socio-Economic Development. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(05), 25–38. https://doi.org/10.55529/jpps.25.25.38
72. Amitava Das. (2021). English Language Invasion of COVID-Terms: How the Pandemic Affects other Languages and Cultures. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 1(01), 13–21. https://doi.org/10.55529/jlls.11.13.21
73. Bhat, R. M. . (2022). An Analytical Study of the Kushan Rule in Kashmir. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(04), 9–14. https://doi.org/10.55529/jpps.24.9.14
74. Bhat, R. M. . (2022). Queen Yasovati: A Descriptive Study on her Leadership in the Kingdom of Kashmir. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(05), 11–17. https://doi.org/10.55529/jpps.25.11.17
75. Dar, S. A. . (2022). Role of E-governance in Higher Education in Jammu and Kashmir. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(04), 1–8. https://doi.org/10.55529/jpps.24.1.8
76. Dar, S. A. . (2022). The Relevance of Taylor's Scientific Management in the Modern Era. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(06), 1–6. https://doi.org/10.55529/jpps.26.1.6
77. Dar, S. A. ., & Lone, D. N. A. . (2022). Uniform Civil Code: Why Implementation is a Himalayan Task. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(06), 7–13. https://doi.org/10.55529/jpps.26.7.13
78. DR. SANJAY JOHARI. (2021). Caste Conflict In Vijay Tendulkar's Play 'Kanyadan'. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 1(02), 7–11. https://doi.org/10.55529/jlls.12.7.11
79. Dr. Sanjay Pandit Kamble. (2022). Sujata Parashar's The Temple Bar Woman: A Study in Revenge Tale. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(02), 1–4. https://doi.org/10.55529/jlls.22.1.4
80. Haneen Ali Haleem, & Wael Mohammed Abd Elazeez. (2022). Filling in the Gaps: Comparing the Use of Verbal Ellipsis in English and Arabic . Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(04), 41–53. https://doi.org/10.55529/jlls.24.41.53
81. Homssi, M. A. ., Abass Ali, A. ., & Kurdi, A. (2022). The Impact of Political Marketing Via Social Media on Political Participation: An Empirical Analysis in Lebanese Context. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(06), 14–21. https://doi.org/10.55529/jpps.26.14.21
82. Isidor FUH SUH. (2022). Parental Involvement and Pupils' Academic Performance in English Language. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(04), 21–32. https://doi.org/10.55529/jlls.24.21.32
83. Jean Marie F. Pasicolan, Romulo T. Banera, Maria Jessamin A. Catabay, & Darin Jan C. Tindowen. (2021). Enhancing Students' English Language Vocabulary Skills Through An Online Remediation Program. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 1(01), 1–12. https://doi.org/10.55529/jlls.11.1.12
84. John Andoh, Daniel Arkoh Fenyi, Mawuena Komi Zotoku, & William Osei-Appiagyei. (2022). An Ethno-pragmatic Analysis of Insults in Akan Asafo Companies: The Case of Asebu Amantsendo Asafo Company of Abura-Asebu-Kwamankese District,

Ghana. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(05), 14–29. https://doi.org/10.55529/jlls.25.14.29

85. Lone, S. A. . (2022). Reflections of Dr. B.R Ambedkar's Idea of Social Justice. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(05), 18–24. https://doi.org/10.55529/jpps.25.18.24
86. M.D.Thamarai Selvi, & Dr. Aruna Arputha Malar. (2021). A Critical Analysis of Robert Frost Poems. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 1(02), 1–6. https://doi.org/10.55529/jlls.12.1.6
87. Maiden Angel Gamboa, Eliza Stephanie Monteclaro, Jan France Joy Tabbang, Darin Jan Tindowen, & Jennifer Bangi. (2021). English Language Proficiency Of Elementary Pupils. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 1(02), 12–20. https://doi.org/10.55529/jlls.12.12.20
88. Mrs. Vanmathy Remoshan. (2021). Mother Tongue Interference In Writing English As a second Language Among the students of Tamil language. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 1(02), 21–29. https://doi.org/10.55529/jlls.12.21.29
89. Miss. Rameshwari Jayshing Ambawade. (2022). Shobha De's Second Thought: The Cultural and Psychological Conflicts. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(01), 9–12. https://doi.org/10.55529/jlls.21.9.12
90. M.D.Thamarai Selvi, & Dr. Saranya P. (2022). Enhancing the Announcement Text Writing Skills of Nautical Science Students' by Employing Scaffolding Approach. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(02), 5–21. https://doi.org/10.55529/jlls.22.5.21
91. M.D.Thamarai Selvi, & Dr. P. Saranya. (2022). Implementing Error Correction Strategies to Enhance Arts & Science College Students' Writing Skills. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(04), 1–20. https://doi.org/10.55529/jlls.24.1.20
92. M. Zeyad Hashim Mohammed, & M. M. Ahmed Adnan Yaseen. (2022). The Effectiveness of The Brunner Model For Developing Technical Skills For Fifth Year Middle School Students In Art Education. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(05), 1–13. https://doi.org/10.55529/jlls.25.1.13
93. Ordu, Stanley, Okpongette Alexander Sam, & Shote Karena Goodness. (2022). The Thing around your Neck by Chimananda Ngozi Adichie: A Stylistic Perspective. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(03), 7–18. https://doi.org/10.55529/jlls.23.7.18
94. Odukwu, Better, & Ordu, Stanley. (2022). Phonetics Instruction's Effect on Adult Learners and the Production of Second Language Sounds at Ignatius Ajuru University of Education. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(04), 33–40. https://doi.org/10.55529/jlls.24.33.40
95. Rather, A. Y. (2022). A Note on Conception of Aurangzeb Alamgir Religious Policy. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(04), 15–22. https://doi.org/10.55529/jpps.24.15.22
96. SHAIRGOJRI, A. A. . (2022). Russia vs. Ukraine War: India's stance. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(05), 1–10. https://doi.org/10.55529/jpps.25.1.10
97. Sudha Rawat. (2022). Politics of Language and Education: An evaluation of Tamil Separatism in the Sri Lankan civil war. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(01), 1–8. https://doi.org/10.55529/jlls.21.1.8

98. Sana Haider. (2022). Critical Linguistics : Demythlogising Society. Journal of Language and Linguistics in Society(JLLS) ISSN 2815-0961, 2(03), 1–6. https://doi.org/10.55529/jlls.23.1.6
99. Thakur, D. A. ., Kumdesh, M. M. ., & Shivhare, M. S. K. . (2022). The 5s: Key Components of Effective and Dynamic Communication. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(04), 23–31. https://doi.org/10.55529/jpps.24.23.31
100. X., S. S. L. ., R., S. ., A, K., & O, A. J. (2022). Comparative Analysis of Ethanolic Juniperus Thurifera Leaf, Stem Bark and Root Extract Using Gas Chromatography and Mass Spectrometry. Journal of Psychology and Political Science(JPPS) ISSN 2799-1024, 2(04), 32–41. https://doi.org/10.55529/jpps.24.32.41
101. Bhoyar, M. R., Chavhan, S., & Jaiswal, V. (2014). Secure method of updating digital notice board through SMS with PC monitoring system. *IOSR Journal of Computer Science (IOSRJCE), e-ISSN*, 2278-0661.
102. Bhoyar, Mayur Ramkrushna. "Home automation system via internet using Android phone." *InternationalJournal of Research in Science and Engineering. CSE Department, JDIET, Yavatmal* 6 (2015).
103. H. Poddar, V. Roy, M. Bhoyar, A. Gangrade, K. N. Venkata Kowshik and P. Rathod, "Leveraging Context-Aware Fogging for Advanced Remote Patient Monitoring and Healthcare in Modern Life," 2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0, Raigarh, India, 2025, pp. 1-6, doi: 10.1109/OTCON65728.2025.11070467.
104. Bhoyar, Mayur R., and Ravi Verma. "Review Paper on a Lightweight Secure Data Sharing System for Mobile Cloud Computing." *Jour of Adv Research in Dynamical & Control Systems* 10 (2018): 2174-21279.
105. Bhoyar, M. R., Chavhan, S., Kalbande, S., & Thengadi, N. (2015). Heart Attack Detection System Using Android Phone. *Ijfeat International Journal For Engineering Applications And Technology*, *1*(8), 79-82.
106. Bhoyar, M. R., & Jaiswal, V. Secure Method of Updating Digital Notice Board through SMS with Pc Monitoring. *Science (IOSR-JCE) e-ISSN*, 2278-0661.
107. Pathak, M., Navaneetha, K., Bhoyar, M., Holkar, U., Tanna, P., & Deepthi, T. (2025, April). Enhancing cloud service security with key escrow and certificateless elliptic curve cryptography. In *2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0* (pp. 1-6). IEEE.
108. Shukla, P. K., Ananthanarayanan, A., Bhoyar, M., Pahade, A., Tanna, P., & Soujanya, M. (2025, April). A secure key escrow mechanism using ecc for distributed mobile networks and cloud services. In *2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0* (pp. 1-6). IEEE.
109. Navaneetha, K., Mehra, V., Bhoyar, M., Kanthi, K. S., Tanna, P., & Karthik, M. V. (2025, April). Enhancing coverage and energy efficiency in b5g networks through hexagonal tiling and ft-s2es strategy. In *2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0* (pp. 1-6). IEEE.
110. Gupta, S. S., Danghi, P. S., Bhoyar, M., Ahamed, S. A., Tanna, P., & Bhaskarani, N. (2025, April). Optimizing edge server deployment in 5g networks: A forecasting-based approach with ai-driven strategies. In *2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0* (pp. 1-6). IEEE.

111. Kumar, B. V., Sharma, J., Anne, K. R., Khan, S., Rakhra, M., & Bhoyar, M. (2025, February). Blockchain-Powered Solutions for Carbon Neutral and Sustainable Economies. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 1510-1515). IEEE.
112. Yamsani, N., Kaur, A., Sarasu, P., Khan, S., Singh, H. K., & Bhoyar, M. (2025, February). Machine Learning Applications in Inflation Forecasting: A Comparative Study of FAVAR and BVAR Models. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 1-5). IEEE.
113. Kumar, K. S., Anne, K. R., Khan, S., Rakhra, M., & Bhoyar, M. (2025, February). Blockchain-Enabled Smart Contracts for Transparent and Sustainable Supply Chains. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 1482-1488). IEEE.
114. Yamsani, N., Kant, V., Sarasu, P., Khan, S., Kaur, B., & Bhoyar, M. (2025, February). Data-Driven Financial Services: Advancing Payment Systems Through Fintech Innovations. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 1506-1509). IEEE.
115. Jagadish, S., Verma, G., Anne, K. R., Khan, S., Singh, H. K., & Bhoyar, M. (2025, February). The Role of AI in Rational Expectations and Behavioral Economics. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 1502-1505). IEEE.
116. Ravi, K., Bhuria, R., Sarasu, P., Khan, S., Kaur, B., & Bhoyar, M. (2025, February). AI-Driven Predictive Modeling for Real-Time Economic Forecasting. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 1477-1481). IEEE.
117. Chukka, N. D. K. R., Kaliappan, S., Maranan, R., Dhal, P. K., Mounika, A., & Bhoyar, M. (2025, February). The Rise of Digital-First Banking: Fintech Innovations Shaping the Future. In *2025 International Conference on Technology Enabled Economic Changes (InTech)* (pp. 1025-1029). IEEE.
118. Dr. Nimisha Beri, Mayur Bhoyar, Mr. Ashish B. Samarth, Mr. Sumit R. Raut. (2024). ENDURING BELIEFS AND EVOLVING PRACTICES: THE INFLUENCE OF MATHEMATICS TEACHERS' BELIEFS ON INSTRUCTIONAL QUALITY AND STUDENT PERFORMANCE. Utilitas Mathematica, 120, 1255–1267.
119. Dr. Parminder, Mr. Sumit R. Raut, Mayur Bhoyar, Mr. Ashish B. Samarth. (2024). HARMONIZING NUMBERS AND NOTES: ENHANCING MATHEMATICAL MODELING WITH MUSICAL RHYTHMS IN TEACHER PROFESSIONAL DEVELOPMENT. *Utilitas Mathematica*, *120*, 1268–1277.
120. Mayur Bhoyar, Mr. Sumit R. Raut, Mr. Ashish B. Samarth, Dr. Anoop Beri. (2024). Cross-Cultural Examination of Cognitive Flexibility in Arithmetic: Replicating Rathgeb-Schnierer and Green's Methodology among Asian Language-Speaking Students. *Utilitas Mathematica*, *120*, 1218–1231.
121. Mayur Bhoyar, Mr. Ashish B. Samarth, Mr. Sumit R. Raut, Dr. Anoop Beri. (2024). DECODING THE GEOMETRIC PROOF: A RUBRIC-BASED ANALYSIS OF CONGRUENT TRIANGLE REASONING ERRORS AMONG ASIAN STUDENTS. *Utilitas Mathematica*, *120*, 1232–1243.
122. Mayur Bhoyar, Mr. Ashish B. Samarth, Ravshan Nurimbetov, Mr. Sumit R. Raut, Dr. Anoop Beri. (2024). ASSESSING MATHEMATICAL MODELING PROFICIENCY IN K-12 EDUCATORS: INSIGHTS FROM THE MATHEMATICAL MODELING KNOWLEDGE SCALE (MMKS) IN ASIA. *Utilitas Mathematica*, *120*, 1244–1254

123. Viswanathan, Venkatraman. "Pioneering Ethical AI Integration in Enterprise Workflows: A Framework for Scalable Team Governance." Available at SSRN 5375619 (2024).
124. Viswanathan, Venkatraman. "Embedding Ethical Principles into Generative AI Workflows for Project Teams." (2024).