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# | RESEARCH ARTICLE

# **Improved Advertising Using SEO Powered by Neural Networks**

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#### ABSTRACT

Neural networks are optimizing content shaping and understanding. Going beyond internet forecasting reaching heights of real time prediction is made possible by SEO using these automated tools. By automating content production and adjusting methods to match changing search engines, Al-powered SEO tools revolutionize digital marketing. Real-time campaign modifications and highly customized consumer experiences are made possible using natural language processing, GPT models, and predictive analysis. Artificial intelligence and deep learning powered SEOs improve intelligence in many areas of the advertising industry. The current study focuses on the algorithms used behind the Al-powered SEOs to get the desired results. A literature review to understand SEO in the current markets, budget ad campaigns accordingly. It uses neural network methods to calculate the advertisement launch and conversion rates. The study takes a precise quantitative approach to optimize the ad campaign, and improvise the results of it using budgeting, and this in turn to analyse the Click through rates and conversion rates of the customers using EVs. The research aims to implement neural network involving Relu activation function and sigmoid activation to predict the probability of customers opting for a test drive.

# **KEYWORDS**

Neural Networks, Predictive Modelling, Mathematical formulation, Digital marketing, Automotive Industry, Relu activation, sigmoid function, Search Engine Optimization, Python, Conversion rates.

## | ARTICLE INFORMATION

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### 1. Introduction

Understanding Search Engine Optimization is a modern method of conducting ecommerce businesses, where the customer is completely digital. This applies to a large scale of customers and products from cosmetics to automotives. Strategies such as sales funnels-E-A-T (Experience, Expertise, Authoritativeness, Trustworthiness), Content Silos, Internet based content mapping, Predictive analytics are some popular strategies which are used to increase content visibility. Artificial Intelligence has become a strong yard to execute these and aid businesses in the research about customer segmentation, understanding, audience targeting, ad creative optimization, ad placement and bidding, personalization, delivery to ad tracking and predictive analysis. In this paper the research aims to explore SEO powered by neural networks in Predictive analysis considering the differences between search engines, factors influencing rankings, and website optimization strategies. The main aspects include search engine accessibility, modifying HTML and content on the websites and enhancing vital keywords with code. Backlinks are inbound links that promote ranking enhancement, emphasizing the 2015 implementation of mobile searches as a key component of internet initiatives. Search Engine Mechanics, such as Understanding search engines crawl, index, and rank websites based on relevancy and retrieval processes. The research paper showcases AI tools to power SEOs and compares their performance in the automotive industry, focusing on the most common scenario of a new car launch. It uses neural network methods and calculates the advertisement launch and conversion rates. It emphasizes the importance of tailoring SEO strategies to individual search engine preferences. In the following sections an in detail mathematical representation of a most common case study is presented in a novel approach. This proves the marvel of ecommerce using new techniques in deep learning approaches, simplified to a universal approach.

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#### 1.1 Background

The new paradigm of digital marketing is Search Engine Optimization techniques, using Artificial Intelligence and Deep neural networks. It is allowing budgeting adjustments and tailoring successful and profit making businesses. With an adept and intense mathematical or statistical orientation in its execution, trust building and sales conversions have become the most common scenarios. In terms of web development, As Google continuously refines its algorithm through updates such as Panda, Penguin, Rank Brain, and BERT, businesses must adapt their SEO strategies to remain competitive. By being aware of Google's changing algorithm, marketers can apply SEO strategies that maximize their online presence while adhering to search engine standards (Rowley). By bringing automation, data-driven insights, and sophisticated personalization strategies, artificial intelligence (Al) has greatly improved search engine optimization (SEO). Al-powered solutions improve technical SEO elements like website performance, indexing, and mobile friendliness as well as keyword research and content relevancy. Additionally, by examining patterns of behaviour, enhancing accessibility, and providing predictive analytics to improve search rankings, Al improves user experience. More relevance and accuracy are ensured by machine learning algorithms that dynamically modify search results based on user intent, like Google's Rank Brain. Businesses may sustain great online presence by streamlining SEO operations with Al-driven link-building tactics and automated content creation.

#### 1.2 Deep Learning Strategies In Digital Marketing

Artificial Intelligence (AI) is fundamentally transforming mundane SEO and digital marketing especially taking over routine tasks, enabling data-driven decision-making, and delivering highly personalized user experiences. At the core of this transformation are the advanced Natural Language Processing (NLP) models particularly transformer-based architectures like BERT and GPT which empower search engines to understand context, user intent, and semantic relationships rather than relying solely on keyword frequency. Models like Google's Rank Brain and BERT analyse query structure and behavioural patterns to return more relevant search results, while generative models such as ChatGPT use attention mechanisms and Reinforcement Learning with Human Feedback (RLHF) to produce context-aware, ethically aligned content for scalable SEO and marketing efforts. In practice, Al-driven platforms like Surfer SEO, Clear scope, SEMrush, and Jasper leverage these models to analyse vast datasets including competitor strategies, search intent, and user engagement to recommend high-performing keywords, optimize content readability, and improve backlink strategies. Technical SEO is also being enhanced through automation in structured data validation, page speed optimization, mobile compatibility checks, and broken link detection, reducing manual workload and improving website performance. With the rise of voice assistants and smart devices, AI further supports conversational content formatting to improve voice search optimization. Due to humungous usage in all possible areas of neural networks, the digital marketing faces the threat of redundancy and similarities of content. However, the approaches are standard, and can be used to improve conversion rates, and financial decision making of the businesses, the current case study focuses more on the predictive analytics of an ad campaign to budget according to the Return on Investments.

### 2. Technical Results

#### 2.1 Predictive Analytics: Mathematical Formulations

Another facet of predictive analytics is mathematical grounding, and machine learning algorithms to forecast future outcomes based on historical data. To get a meaningful insight of the data from the patterns, with mathematical underpinnings, predictive analysis is all about using past data to make insightful, well-informed forecasts about the future. It makes use of methods like statistical modelling, machine learning, and probability to find connections and patterns that aren't immediately obvious. One straightforward example is linear regression, which uses a formula that illustrates their relationship to predict one thing (like website traffic) based on another (like ad expenditure). Neural networks extend this concept for more complicated issues by overlaying numerous tiny mathematical operations to find patterns in huge and frequently disorganized datasets. As more data is collected, these models get better at making predictions by reducing mistakes through techniques like gradient descent. Predictive analysis offers companies a strong, mathematical method to keep ahead of the curve, whether it is for predicting SEO trends, customizing product recommendations, or instantly identifying fraud. The logistic regression model outputs probabilities using the sigmoid function:

Equation: 1
$$P(y = 1 \mid x) = \frac{1}{1 + e - (wTx + b)}$$

Here, $x \in R^n$  is the feature vector,  $w \in R^n$  is the weight vector, and b is the bias term. The model is trained by minimizing the binary cross-entropy loss function:

#### Equation: 2

$$L(w,b) = -\frac{1}{m} \sum_{i=1}^{m} \left[ y^{(i)} log(\hat{y}^{(i)}) + (1 - y^{(i)}) log(1 - \hat{y}^{(i)}) \right]$$

where  $\hat{y}^{(i)}$  is the predicted probability for instance i, and m is the number of training samples. Gradient descent is typically used to optimize this loss, adjusting  $\mathbf{w}$  and  $\mathbf{b}$  to minimize prediction error.

To capture non-linearities and complex user behaviour patterns, advertisers often deploy neural networks, which extend logistic models with multiple layers of transformations. In a neural network, each hidden layer computes:

$$a(l) = \sigma(\boldsymbol{W}^{(l)}a^{(l-1)} + \boldsymbol{b}^{(l)})$$

where  $\sigma$  is an activation function such as ReLU or sigmoid,  $\mathbf{W}^{(l)}$  and  $\mathbf{b}^{(l)}$  are the weight matrix and bias vector of layer l, and a(l-1) is the output from the previous layer. These models are trained using backpropagation, an algorithm that computes gradients of the loss function with respect to each parameter using the chain rule. In digital advertising, these predictive models power Real-Time Bidding (RTB) systems, where advertisers bid on ad impressions in milliseconds. Bids are dynamically adjusted based on the predicted value of a user interaction. For instance, if the expected Click-Through Rate (CTR) is p, and the expected Value per Click (VPC) is v, then a simple bid value is computed as:

$$Bid = p \times v$$

This equation allows advertisers to optimize budget allocation based on ROI expectations. Over time, models are refined using techniques such as multi-armed bandits or reinforcement learning, which balance exploration (trying new strategies) and exploitation (capitalizing on known successful actions) for continual performance improvement.

#### 2.2 Predictive Analytics in Advertising a New Car Launch Scenario: Campaign Objective and Strategy

The boom of artificial intelligence has led to its adoption in Search Engine Optimization (SEO) and predictive analytics in the world of ever-changing digital marketing. The current section examines a large-scale ad campaign, of launching an EV by an automaker. The metrics such as individualized user interaction, and advertising reach by machine learning models and statistical methods. The aim is to inculcate neural network strategy into the digital marketing, with the mathematical modelling. The primary goal is to maximize test drive bookings, and pre orders and reach a certain level of Return on Ad Spend, with budgeting the ad campaign. Also, to code for successful digital performances, increase qualified leads and set up a scalable framework that is suitable for future launches.

The method following is a framework of predictive modelling works with any given website.

User Visit → Data Capture → Send to Model → Predict Score →

- High Intent → Personalize Site + High Ad Bid
- Low Intent → Softer CTA + Add to Retargeting
- Conversion Data → Sent Back to Model → Retraining

Figure 1: Framework of implementation.

The above case is tested using a python code, following the framework of predictive modelling. The main focus is to analyse the use of predictive modelling in the sample data, and analyse the results of it using confusion matrix and f1 score. The neural network model aims to predict the probability of customer booking a test drive based on the behaviour and factors of customer segmentation, while browsing an automotive website. The code utilizes numpy modules to generate sample data, that consists of all combinations of time spent on the website, pages visited and information viewed, also demographic locations. This data is used to train the neural network model. The first layer uses RELu activation, which helps to identify complex patterns in the data. These patterns might involve how different factors combine to influence a person's decision. The output layer uses sigmoid function to give a probability score of showing the likelihood of customer booking a test drive. The model is trained using an optimizer that balances learning quickly and accurately, and it's checked along the way to make sure it's not just memorizing the training data. When tested, it provides useful metrics like accuracy and precision, helping marketers understand how well it predicts bookings. With this approach, marketing teams can better spot potential buyers, spend their advertising budget

smarter, and increase the chances of converting website visitors into actual test drives. The following pictorial representations show the results of the python code.

```
Epoch 28/30
18/18 -
                         — 0s 6ms/step - accuracy: 0.9966 - loss: 0.0104 - val_accuracy: 1.0000 - val_loss: 0.0013
Epoch 29/30
18/18 -
                          - 0s 6ms/step - accuracy: 0.9991 - loss: 0.0040 - val accuracy: 1.0000 - val loss: 0.0013
Epoch 30/30
18/18 -
                         9s 6ms/step - accuracy: 0.9942 - loss: 0.0156 - val_accuracy: 1.0000 - val_loss: 0.0013
Test Accuracy: 1.00
10/10 -
                          - 0s 7ms/step
Classification Report:
                           recall f1-score
              precision
                   1.00
                             1.00
                                       1.00
                                                   300
    accuracy
                                       1,00
                                                   300
   macro avg
                   1.00
                             1.00
                                       1.00
                                                   300
weighted avg
                   1.00
                             1.00
                                       1.00
                                                   300
Confusion Matrix:
[[300]]
```

Figure 2: Results of the code.

The training output shows that the neural network learned the data very quickly and effectively. Over the course of 30 training epochs, the model's accuracy steadily improved, starting from around 99.8% and reaching nearly 100%. Simultaneously, the loss—which measures how far the model's predictions are from the actual results—consistently decreased, indicating that the model was minimizing errors during training. The validation accuracy remained perfect (100%) from early on, suggesting the model generalized well to unseen data during training.

By the end of training, the model achieved an almost perfect test accuracy of 100%, which means it correctly predicted whether customers booked a test drive in nearly every case. The classification report further confirms this, showing perfect precision, recall, and F1-scores—all key metrics that reflect the model's ability to correctly identify both positive cases (bookings) and avoid false alarms.

In summary, these results indicate the model is highly effective at predicting test drive bookings based on user behaviour features. However, such near-perfect performance can sometimes signal overfitting, especially if the dataset is small or not diverse enough, so further validation on new or more varied data would be advisable before deployment.

#### 3. Conclusion

The integration of these mathematically grounded AI techniques in advertising has shown to boost conversion rates, improve budget efficiency, and enhance customer targeting through hyper-personalized experiences. Leading platforms like Google Ads, Meta, and Amazon Advertising now embed these models in tools such as Smart Bidding, Performance Max campaigns, and personalized ad placements. As a result, predictive analytics not only optimizes individual campaign performance but also reshapes strategic planning in digital marketing by making outcomes more measurable and adaptive. This case study illustrates predictive analytics and SEO driven by AI have transformed modern advertising with a neural network framework implemented into the general SEO strategies. The ability to harness real-time user data, automate optimization tasks, and predict conversion behaviour allows advertisers to deploy hyper-targeted campaigns with greater ROI. For industries like automotive where purchase decisions involve high consideration and long sales cycles such intelligent systems are beneficial and essential for market competitiveness and brand positioning. Al will play a bigger part in digital marketing as it develops, allowing for increasingly more sophisticated customisation, performance predictions, and the implementation of flexible strategies.

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