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Article

Application of convolutional neural networks for mobile internet forecasting in Colombia

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Abstract: The growth of mobile Internet has facilitated access to information by minimizing geographical barriers. For this reason, this paper forecasts the number of users, incomes, and traffic for operators with the most significant penetration in the mobile internet market in Colombia to analyze their market growth. For the forecast, the convolutional neural network (CNN) technique is used, combined with the recurrent neural network (RNN), long short-term memory network (LSTM), and gated recurrent unit (GRU) techniques. The CNN training data corresponds to the last twelve years. The results currently show a high concentration in the market since a company has a large part of the market; however, the forecasts show a decrease in its users and revenues and the growth of part of the competition. It is also concluded that the technique with the most precision in the forecasts is CNN-GRU.

Keywords: artificial intelligence; competition; forecast; mobile internet; telecommunications market

1. Introduction

The digital divide is a global challenge that affects millions of people, limiting their access to information. Telecommunications are a fundamental tool to close this gap and promote digital inclusion. This encourages economic development, access to information and services (Wang and Sun, 2022). Thus, governments promote the entry of new operators into the market to increase supply and reduce prices, which additionally leads to an increase in coverage, infrastructure and services. Competition between mobile operators is essential for innovation and price reduction. By competing for consumers, companies are forced to offer better quality in their services, which leads, among other things, to higher connection speeds and more coverage. Additionally, operators develop new technologies and services to differentiate themselves from their rivals, with more attractive rates (Fiedler et al., 2017, Pedraza et al., 2024).

Mobile networks have undergone considerable evolution over the decades. With advances in electronics and the Internet, mobile services have become essential for work, education, and leisure in our daily lives. However, like any other service, mobile networks need regulation by government authorities in each nation. This creates an active market where service providers and regulators must constantly renew their policies and regulations to manage traffic, prices, and services effectively. Understanding market behavior under particular regulations or introducing new services or competitors is challenging (Yang and Kawashima, 2024). Companies like Cisco project that monthly global mobile data throughput will exceed hundreds of exabytes. To meet that need, providers must either increase their investments in acquiring more bandwidth and expanding capacity or implement revolutionary pricing strategies, which drive up operating expenses. They face intense competition to attract subscribers to their network services as the market evolves (Cadena et al., 2024; Zhang, 2022).

Most of the data forecasting techniques focus on studying customer churn. Logistic regression is widely used for prediction with a training data set. Decision trees are also used as predictive learning techniques in business analytics. These generate high interpretability and a robust rule method. They have been used in applications such as future stock markets and customer-related decisions (Cadena et al., 2024; Manzoor et al., 2024). Techniques such as random forest, support vector machine, gradient boosting, extreme gradient boosting, light gradient boosting machines, and boosted trees have also been used to predict customer churn in telecom operators (Chang et al., 2024; Krishna et al., 2024).

Additionally, models have been used to forecast traffic in mobile operators, ranging from classical models such as multiplicative seasonal ARIMA (Guo et al., 2009), as well as more elaborate models such as Holt-Winters, TBATS, TensorFlow Probability, RNN, LSTM, bidirectional LSTM, CNN (Alzalam, et al., 2024; Kochetkova et al., 2023) and federated learning (Pavlidis et al., 2024) for forecasting in 5G networks.

Artificial intelligence methods like deep learning and algorithms like CNNs are used to classify problems in telecom datasets. Telecom services also employ RNNs for prediction. In addition, a hybrid deep learning architecture using CNN and LSTM has been proposed. In Lai et al. (2020), they employ LSTM and RNN schemes to obtain good results. Most Artificial Intelligence techniques have been used to forecast sales or customer churn in mobile services, and random forests or decision trees are applied (Wisesa et al., 2024). Techniques such as CNN and RNN are used for classification problems in mobile services (Cadena et al., 2024).

This paper presents the forecast using CNN techniques at access numbers, income, and data traffic for the mobile internet market in Colombia. CNN is well known for its ability to automatically learn and extract features from the raw sequence, which, combined with other techniques, such as those presented in this study, that capture the long and short-term dependence of the time series data, have shown adequate prediction capabilities for mobile networks (Huang et al., 2017), (Shawel et al., 2022). The models' training corresponds to the information from the launch of this service in 2012 until 2024, combining the prepaid and postpaid services.

The structure of this paper is as follows: Section 2 explains the methodology used, the characteristics of the data used, and the forecasting techniques implemented. Section 3 shows and discusses the forecasts' results. Finally, Section 4 presents the conclusion.

2. Methodology

The methodology used in this study is summarized in the diagram in **Figure 1**. Information on mobile operators' income, traffic, and number of users is obtained from Colombia's Communications Regulatory Commission (CRC) (Colombian Communications Regulation Commission, 2024; Hernandez et al., 2024).

The process begins with organizing each operator's data for each variable. Then, the information is cleaned, which is called data preprocessing. Subsequently, the information is prepared through parameter adjustment and data selection for training and evaluation. Then, the forecast is made using the CNN-RNN, CNN-LSTM, and CNN-GRU models. Next, the prediction data for income, traffic, and number of users is adjusted and validated. Finally, the output data and the mean absolute percentage error (MAPE) are presented.

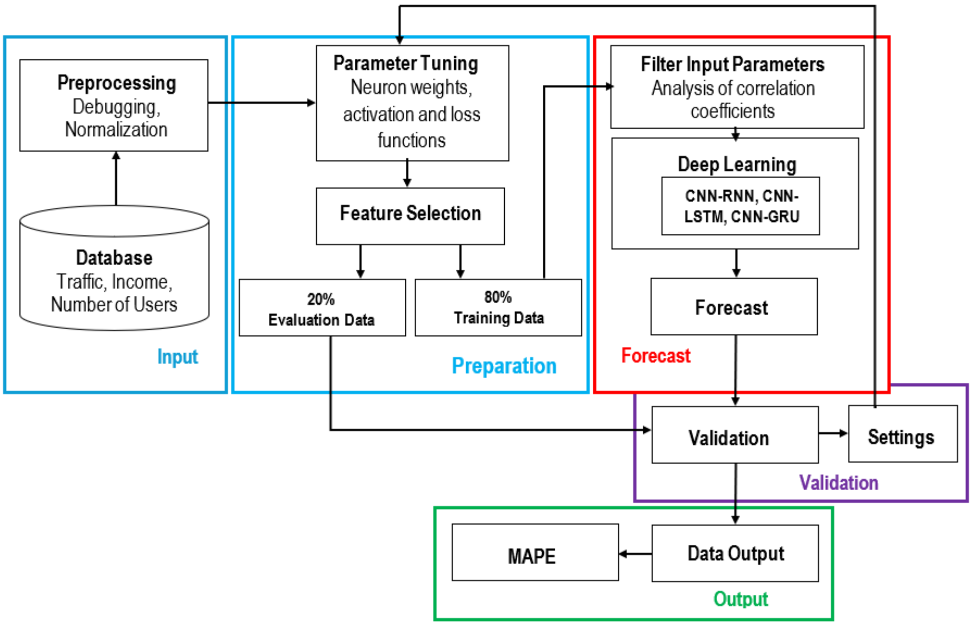

Figure 1. Diagram of the methodology used.

2.1. Data

The data used is for the companies with the highest percentage of penetration in Colombia, which offer postpaid (fixed charge) and prepaid (on-demand) mobile internet service (Colombian Communications Regulation Commission, 2024). Claro has approximately 57% of users, Movistar has around 21%, and Tigo has close to 17%.

The mobile internet data used to train the models are obtained from the CRC and correspond to the sum of the monthly data for prepaid and postpaid services from 2012 to June 2024 (Pedraza et al., 2024).

The main limitations of this study are the data acquisition and the amount of data. The data were acquired from the CRC database, which means that there may be some errors in transcription; however, the entity reviewed and corrected the atypical data. The data amount is based on operators' monthly reporting for approximately twelve years.

2.2. Convolutional neural network—Recurrent neural networks model

RNNs are deep learning models that capture the dynamics of sequences through recurrent connections, which can be thought of as cycles in the network of nodes (Guarascio et al., 2019).

CNN, a type of artificial neural network, has a deep forward propagation architecture and unique generalization ability compared to other networks with fully connected layers; it can learn highly abstract features from data (Ghosh et al., 2020).

Combining RNNs with CNNs takes advantage of CNNs' ability to extract spatial and temporal features from data and RNNs' ability to model long-term dependencies in sequences.

In this architecture, CNNs process the input and extract relevant features. These features are then passed to an RNN, which uses them to model sequential dependencies and make predictions (Dong et al., 2019), as seen in **Figure 2**.

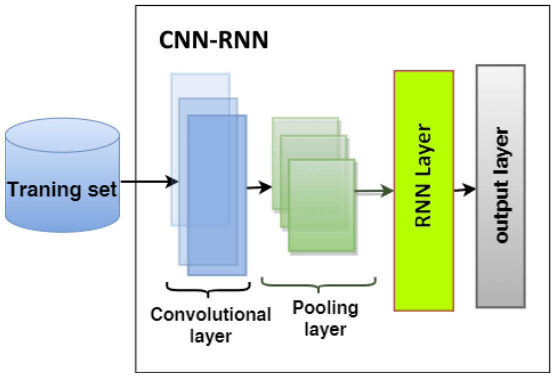

Figure 2. CNN-RNN based model.

2.3. Convolutional neural network—Long short-term memory network model

LSTMs are a particular type of RNN with high performance and a special type of deep learning. The main feature of RNNs is their ability to store information so that they can "remember" previous states and use this information to decide what the next state will be. For this reason, they are suitable candidates for processing time series. However, RNNs can only model short-term dependencies, whereas LSTMs can learn long dependencies, i.e., they have a longer-term "memory" (Liu and Zhang, 2021).

CNN can be highly efficient when features are automatically recovered and trained from one-dimensional sequence data, such as univariate time series data. It is used to understand the input subsequences provided to the LSTM model. As a result, a CNN model can be used in a hybrid model with an LSTM backend, known as CNN-LSTM (Prakash et al., 2023).

The structure of a CNN-LSTM can be represented in **Figure 3** (Almulihi et al., 2022).

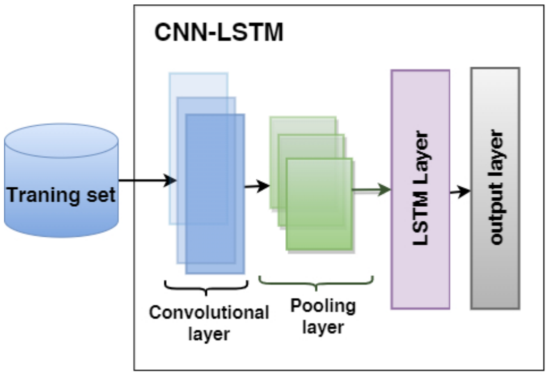

Figure 3. CNN-LSTM Model.

2.4. Convolutional neural network—Gated recurrent unit model

GRUs are a variant of RNNs designed to model long-term dependencies in sequential data more efficiently than LSTMs. GRUs have gained popularity due to their simplicity and computational efficiency compared to LSTMs while maintaining similar performance on many tasks (Chung et al., 2014).

In this architecture, CNNs extract relevant features from the input data. These features are then passed to a GRU layer, which uses them to model long-term dependencies in the data and make predictions (Sharma et al., 2023), as presented in **Figure 4** (Almulihi et al., 2022).

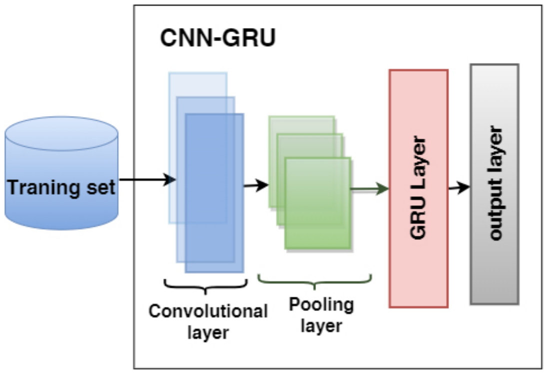

Figure 4. CNN-GRU Model.

3. Results and discussion

Below are the predicted results for each company, which were developed in Python software. Although the training data is from 2012, it is presented from 2018 to facilitate visualization. The training data is in blue, and the predicted data for a given year is in red.

3.1. CNN-RNN model forecasts

Figures 5–7 show the forecasts for the number of users. In Claro, an increase is observed until 2024, and the predicted results show a downward trend. In Movistar, an upward trend is also observed in the training data, and the upward trend is maintained for the predicted data. For Tigo, the number of users is bullish until 2024, and a downward trend is forecast.

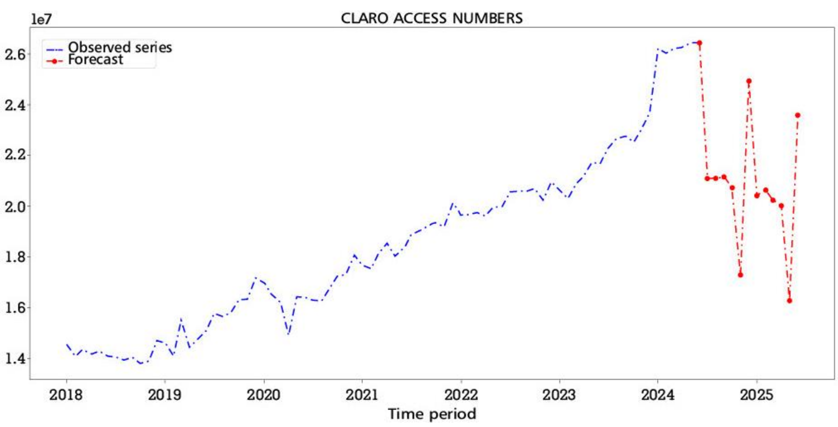

Figure 5. Forecast of the number of users for Claro company.

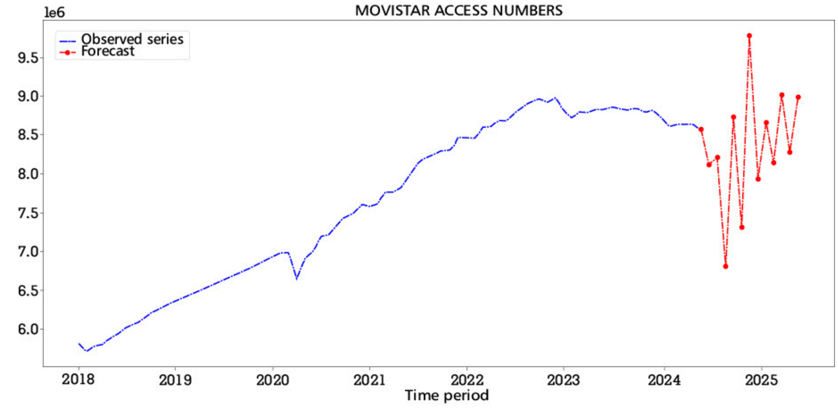

Figure 6. Forecast of the number of users for Movistar company.

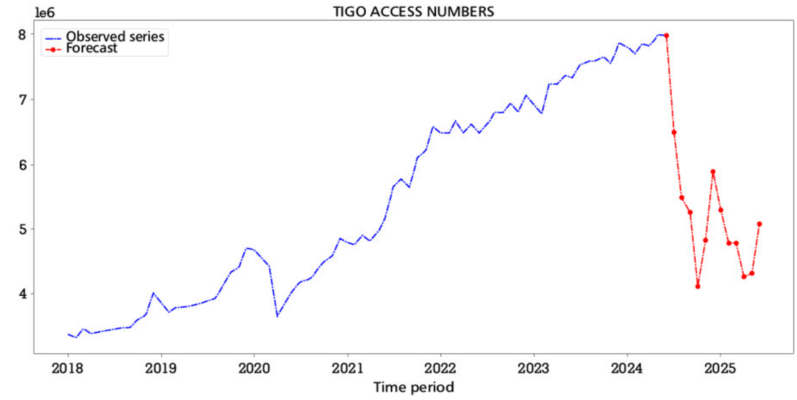

Figure 7. Forecast of the number of users for Tigo company.

Figures 8–10 show the income in Colombian pesos. Claro's income increased until 2024, but a decrease is forecast. Movistar's income increased until 2024, but a sideways trend is forecast. Tigo's income increased until 2024, but a downward trend is forecast.

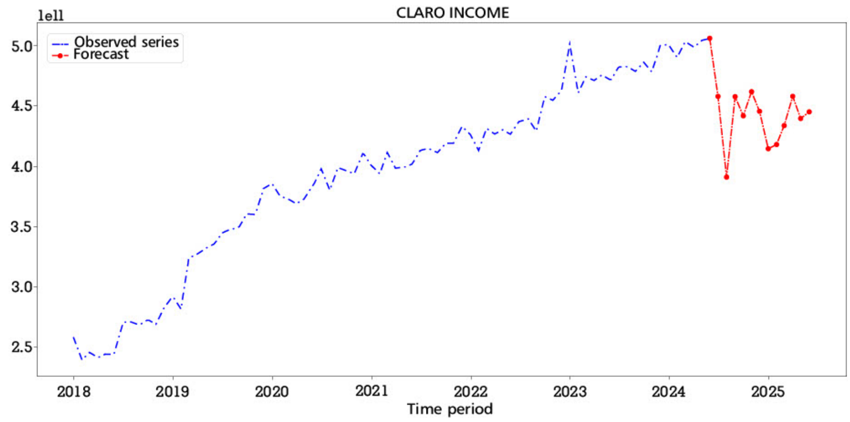

Figure 8. Income forecast for Claro company.

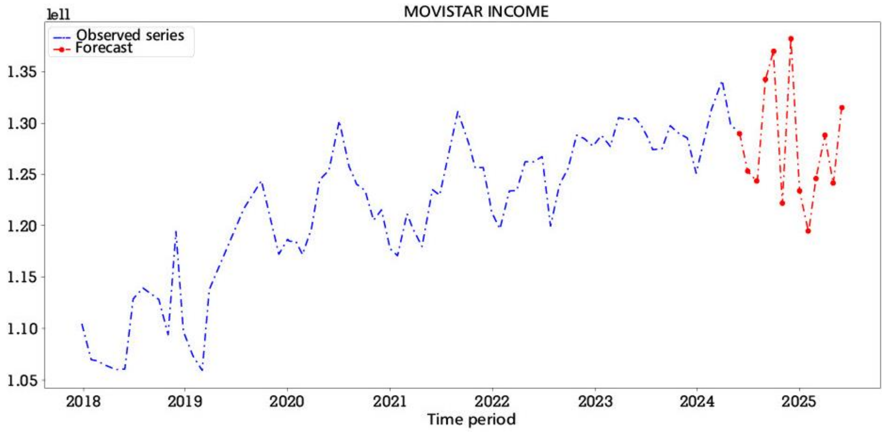

Figure 9. Income forecast for Movistar company.

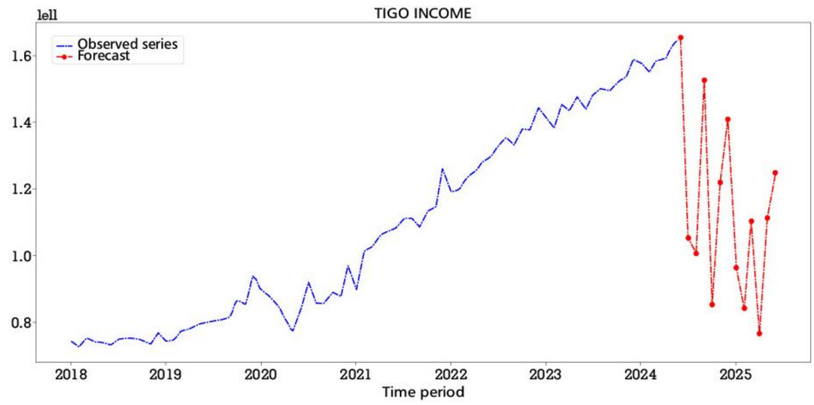

Figure 10. Income forecast for Tigo company.

Figures 11–13 show the traffic in megabytes. Traffic at Claro is expected to increase until 2024, and a lateral trend is forecast. Movistar and Tigo have shown an increase in traffic until 2024, and a decrease is forecast.

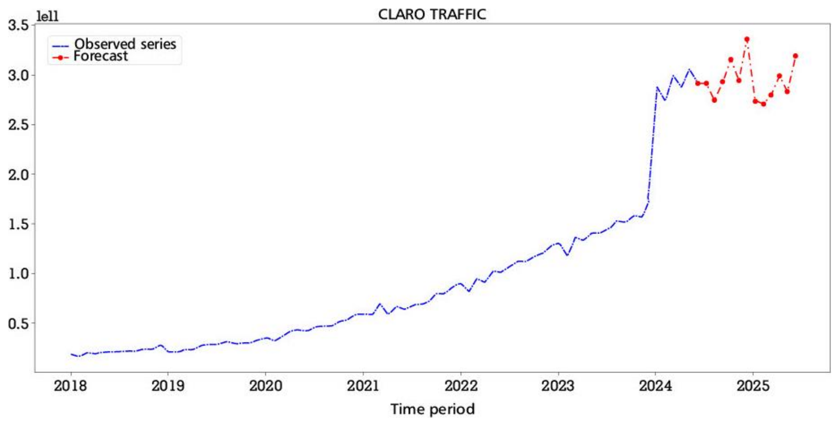

Figure 11. Traffic forecast for Claro company.

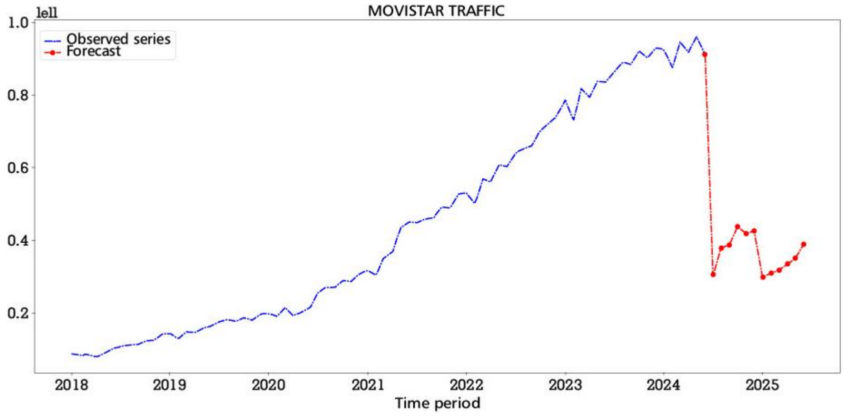

Figure 12. Traffic forecast for Movistar company.

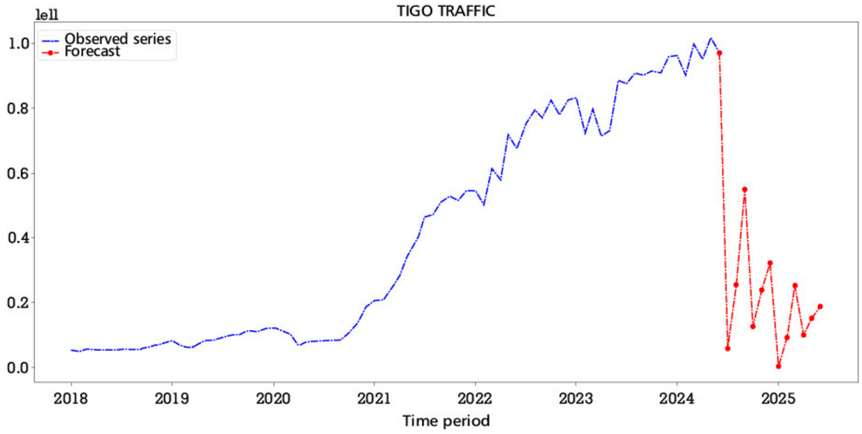

Figure 13. Traffic forecast for Tigo company.

3.2. CNN-LSTM model forecasts

Figures 14–16 show the forecasts for the number of users. Here, Claro is seeing an upward trend until 2024, and a lateral trend is forecast. Movistar is expected to have an upward trend, and in Tigo, although there has been an increase until 2024, it is expected to have a downward trend.

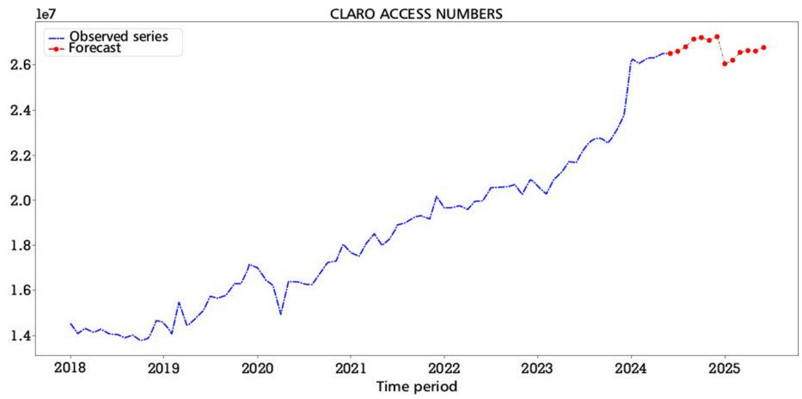

Figure 14. Forecast of the number of users for Claro company.

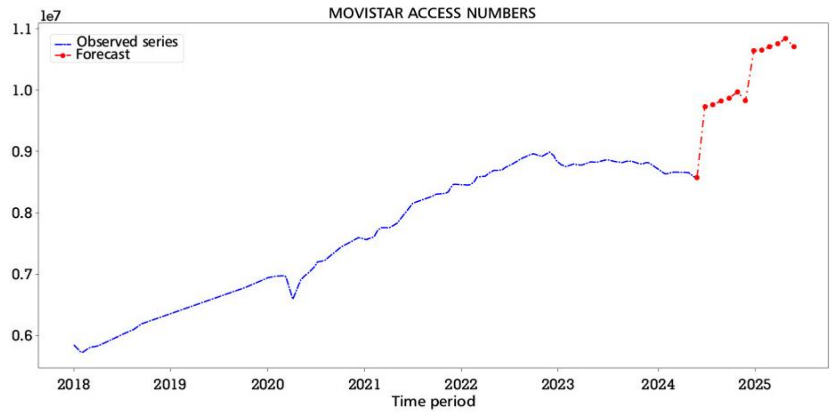

Figure 15. Forecast of the number of users for Movistar company.

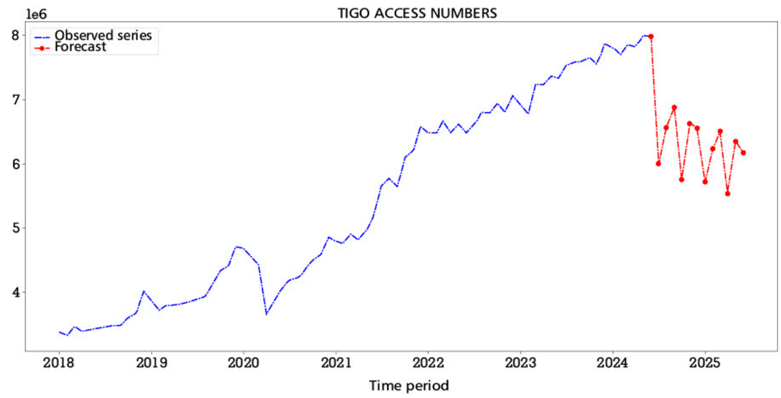

Figure 16. Forecast of the number of users for Tigo company.

Figures 17–19 show the income in Colombian pesos. Claro's income has been steadily increasing through 2024, and the same trend is forecast. Movistar's income has had logarithmic growth through 2024, and an upward trend is forecast. Tigo has seen linear growth from 2020 to 2024; however, a decline is forecast.

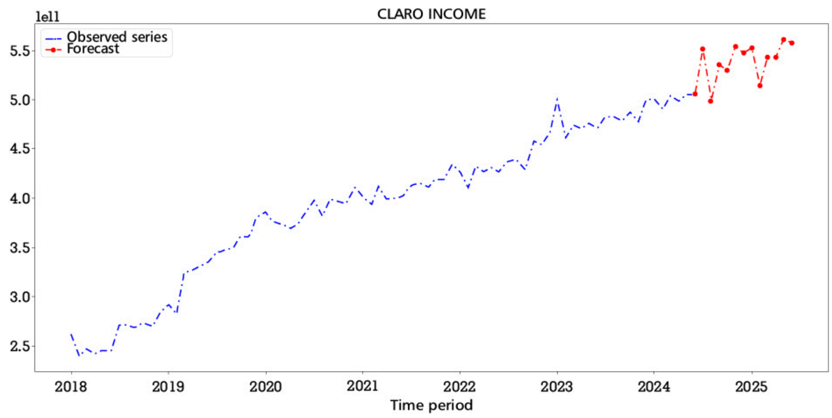

Figure 17. Income forecast for Claro company.

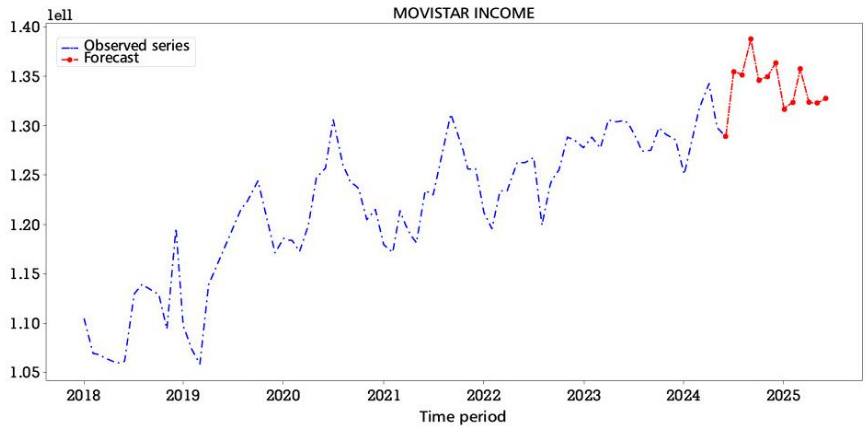

Figure 18. Income forecast for Movistar company.

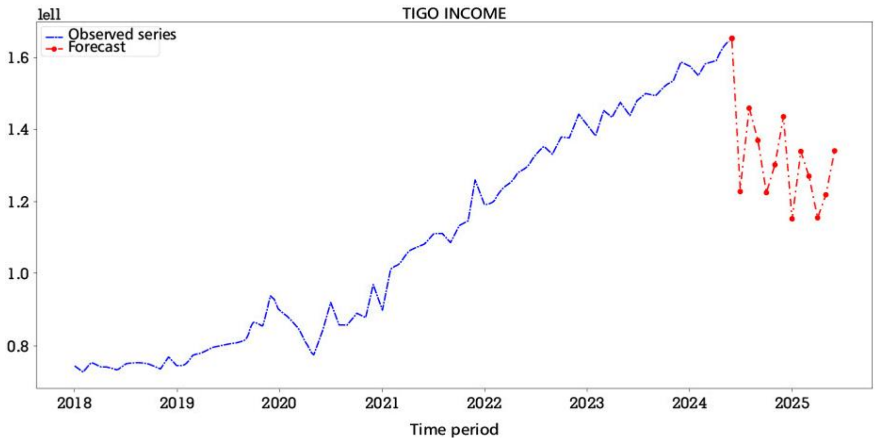

Figure 19. Income forecast for Tigo company.

Figures 20–22 show the traffic in megabytes. Claro and Movistar's traffic increased until 2024, and an upward trend is forecast. Also, traffic at Tigo increased until 2024, and a considerable decrease is forecast.

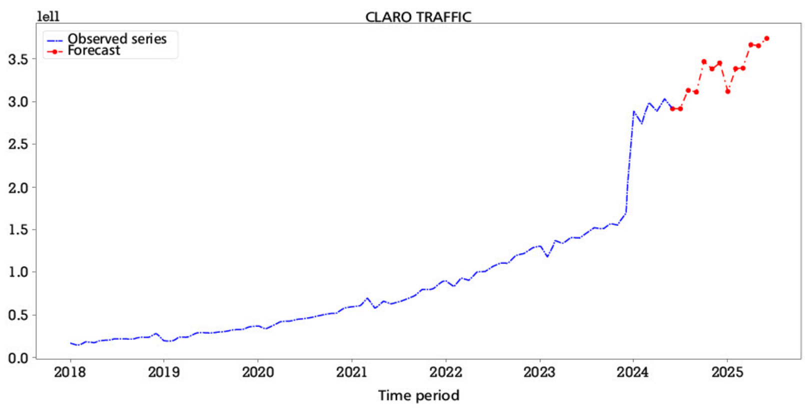

Figure 20. Traffic forecast for Claro company.

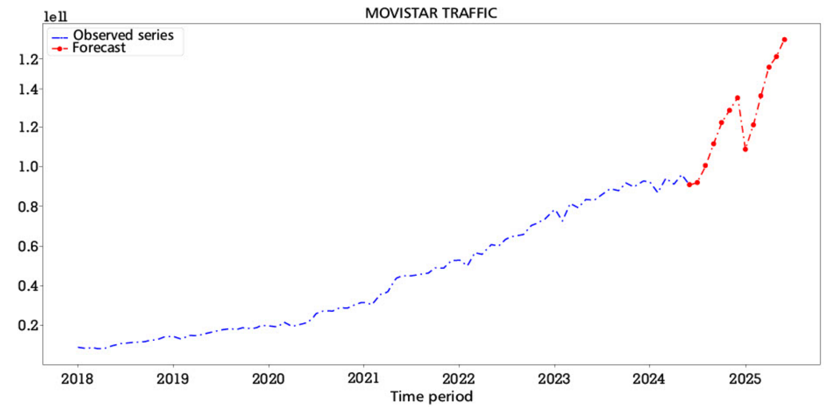

Figure 21. Traffic forecast for Movistar company.

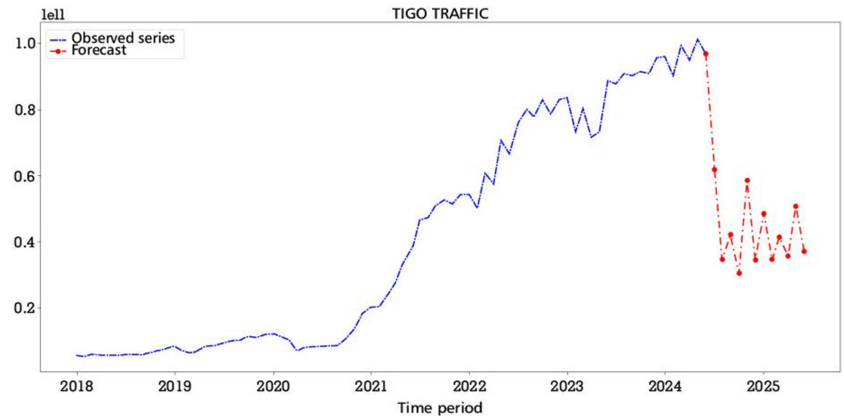

Figure 22. Traffic forecast for Tigo company.

3.3. CNN-GRU model forecasts

Figures 23–25 show the forecasts for the number of users. In Claro, growth has been observed until 2024, and a lateral trend is forecast. In Movistar, slight growth is forecasted after an upward trend until 2024, and then a lateral trend remains. For Tigo, an increase is observed until 2024, followed by a downward trend.

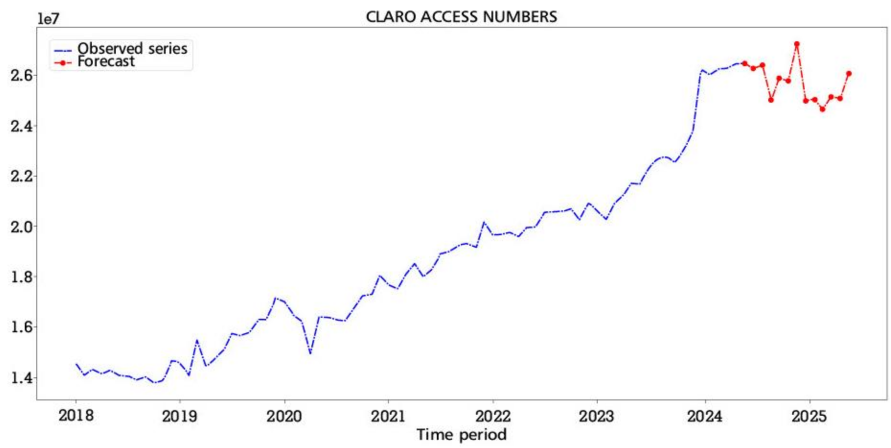

Figure 23. Forecast of the number of users for Claro company.

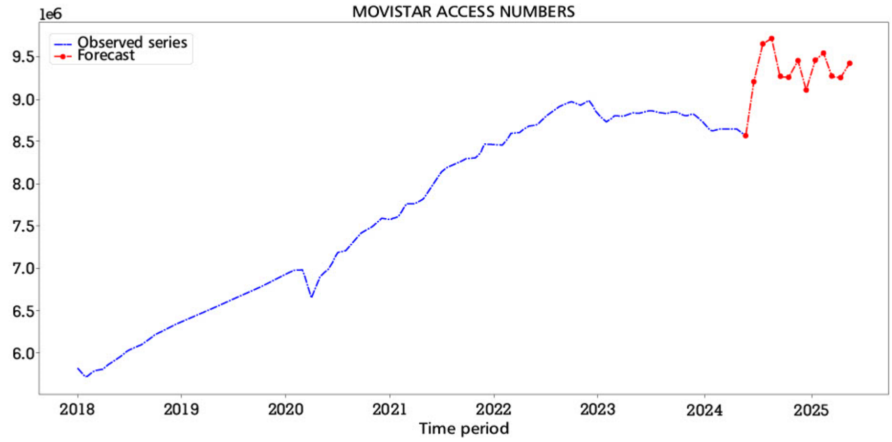

Figure 24. Forecast of the number of users for Movistar company.

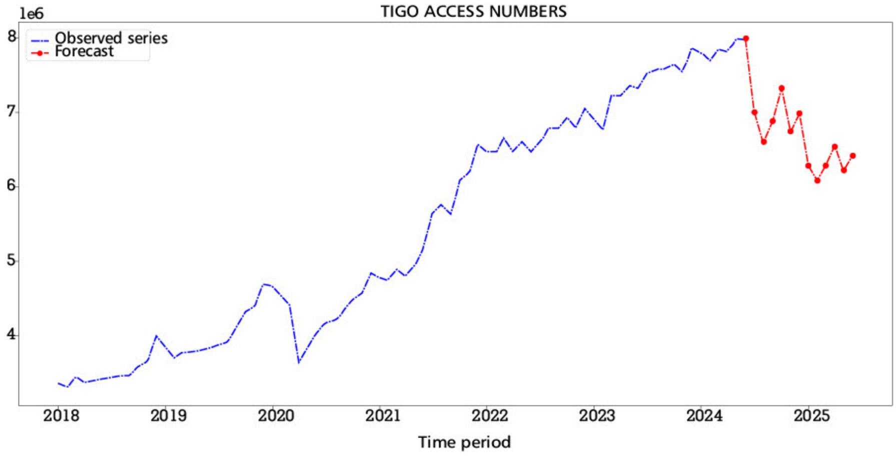

Figure 25. Forecast of the number of users for Tigo company.

In **Figures 26–28**, income is presented in Colombian pesos. The income forecast for Claro and Tigo shows a decline after an upward trend until 2024. After the income growth in Movistar until 2024, an oscillating behavior is forecast.

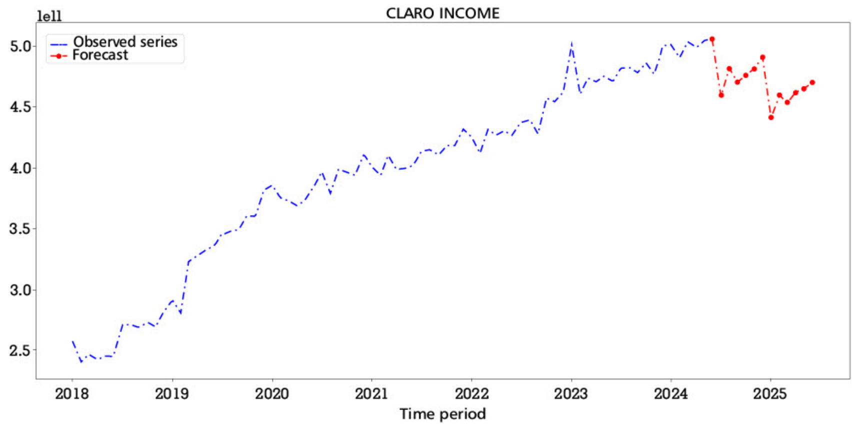

Figure 26. Income forecast for Claro company.

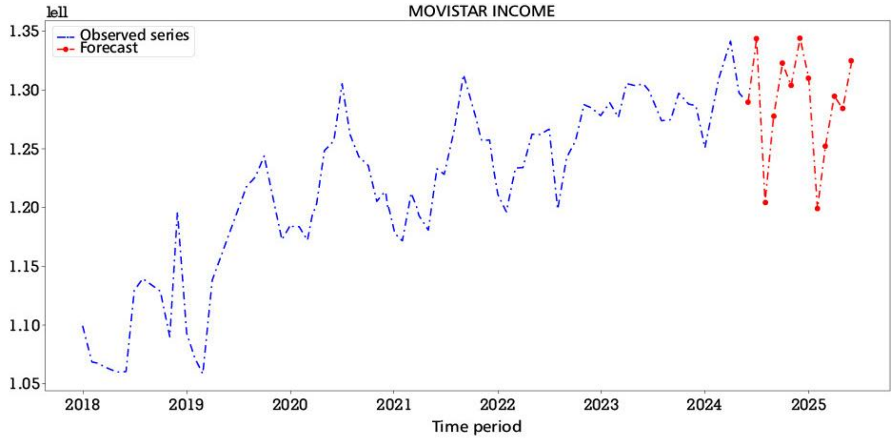

Figure 27. Income forecast for Movistar company.

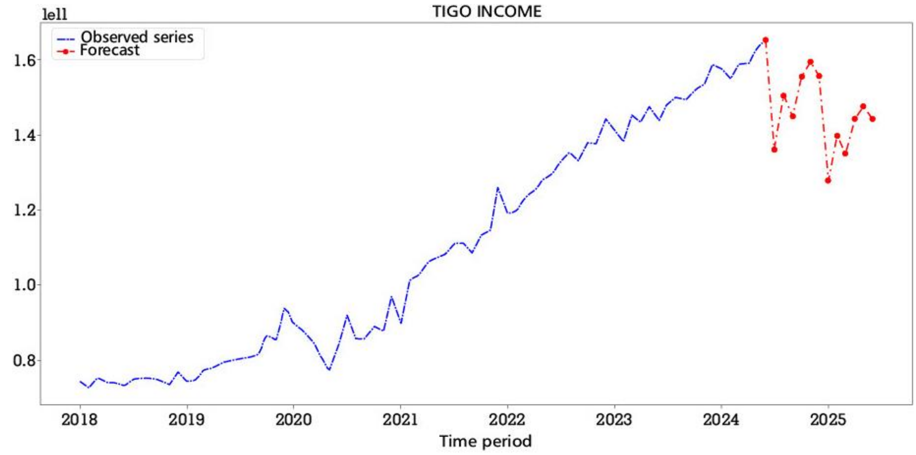

Figure 28. Income forecast for Tigo company.

Figures 29–31 show the traffic in megabytes. Claro has shown an increase until 2024, and a lateral trend is forecasted. For Movistar and Tigo, a downward trend is forecast after growth until 2024.

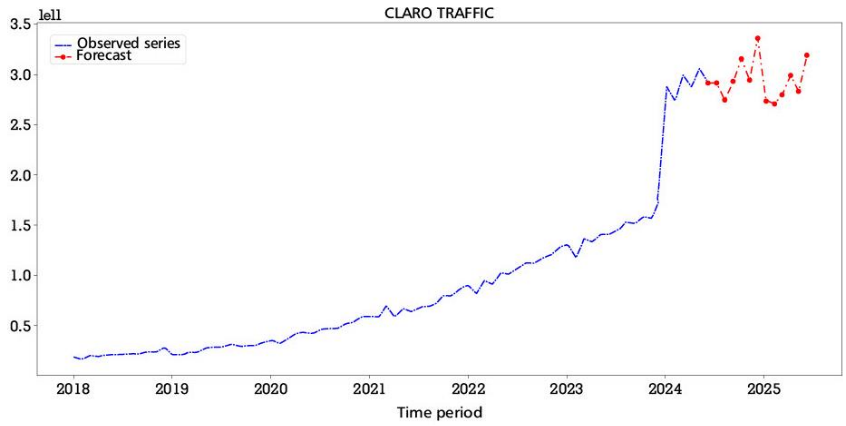

Figure 29. Traffic forecast for Claro company.

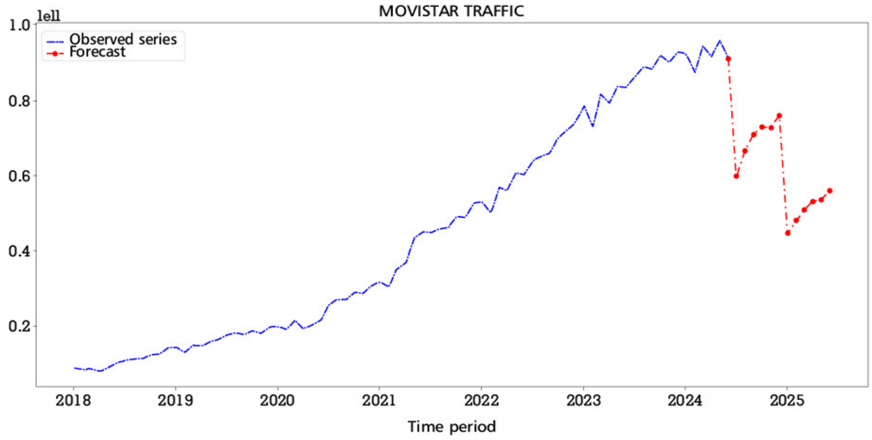

Figure 30. Traffic forecast for Movistar company.

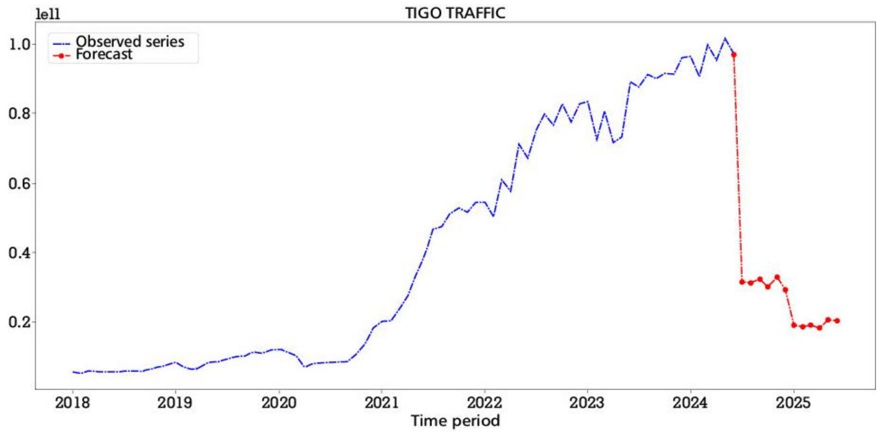

Figure 31. Traffic forecast for Tigo company.

3.4. Discussion

The accuracy of the forecasts obtained is evaluated through the MAPE (Pedraza et al., 2024). **Table 1** presents the MAPE for the number of users, income, and traffic forecasts for each model and company.

Table 1. Mean absolute percentage error for forecasts.

	Claro CNN-RNN	**Claro CNN-GRU**	**Claro CNN-LSTM**	**Movistar CNN-RNN**	**Movistar CNN-GRU**	**Movistar CNN-LSTM**	**Tigo CNN-RNN**	**Tigo CNN-GRU**	**Tigo CNN-LSTM**
Access numbers	17.3	0.678	2.1	19.3	6.49	13.9	45.8	29.7	34.6
Income	11.5	2.15	3.72	5.18	5.63	1.43	33.2	20	26.6
Traffic	52.5	8.14	18.5	57.9	18.8	31.7	73.4	76.8	79.2

From **Figures 5–31** and **Table 1**, the following can be observed:

In the case of the number of users and the income of the Claro company, a decrease is predicted with the CNN-RNN and CNN-GRU models, while for the CNN-LSTM model, they increase. For traffic, an increase is predicted with the CNN-GRU and CNN-LSTM models and a decrease with the CNN-RNN model. The MAPE is lower in all cases with the CNN-GRU model.

Movistar company predicts an increase in the number of users and income for all three models. Regarding traffic, the CNN-LSTM model predicts an increase; however, the CNN-GRU and CNN-RNN models predict a decrease. The CNN-GRU model's MAPE for the number of users and traffic is better than that of the CNN-RNN and CNN-LSTM models; on the other hand, the CNN-LSTM model presents the smallest MAPE for income.

The three models forecast a decrease in users, income, and traffic at Tigo company. The CNN-GRU model's MAPE for the number of users and income is lower, although the CNN-RNN model's is lower for traffic.

4. Conclusion

The telecommunications market forecast, as it relates to mobile Internet, helps to identify the risks at the level of competition that may arise in the market and thus establish a regulatory framework that directly impacts competition and innovation for this sector.

The advantage of using CNN models to forecast the number of users, income, and traffic of mobile internet operators is that they can process large amounts of data in a short time and identify patterns and trends, which facilitates decision-making. For this study, the technique that obtained the highest accuracy in the forecasts concerning MAPE is CNN-GRU.

There is currently a high concentration of mobile Internet services in Colombia. As can be seen in the results obtained, the Claro company has the most significant number of users, income, and traffic on its network. However, with CNNs, a decrease is forecast for the number of users and, therefore, in income. In addition, growth for Movistar company is forecasted using the variables evaluated. This may be due to the regulatory measures taken in the country by the CRC to improve the well-being of users, among which the following stand out: Facilitating access to the mobile number portability resource, as well as the consultation and consistency of the different plans and rates of the operators and the optimization of rates and geographic coverage for automatic national roaming.

Additionally, the recent allocation of radio frequencies to mobile operators for deploying 5G technology was done equitably and with the commitment to increase coverage of the national territory (Ministry of Information and Communications Technologies of Colombia, 2023). As part of the recommendations to reduce concentration in the mobile Internet sector in Colombia, it is suggested that a stable regulatory framework that favors innovation, consumer protection, investment, and competition be maintained and that the quality of service provided by operators be regulated. For this purpose, monitoring and forecasting the market is essential.

Author contributions: Conceptualization, CAH; methodology, CAH; software, LFP; validation, EC and LFP; formal analysis, LFP and EC; investigation, CAH and LFP; resources, LFP; data curation, EC; writing—original draft preparation, EC; writing—review and editing, CAH, EC and LFP; visualization, LFP; supervision, CAH; project administration, CAH; funding acquisition, LFP. All authors have read and agreed to the published version of the manuscript.

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