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*Article*

# An Approach to Forecasting Commodity Futures Prices Using Machine Learning

**Gabriel Schneider de Jesus [1*], Aurélio Faustino Hoppe [1], Andreza Sartori [1], and Valderi Reis Quietinho Leithardt [2,3]**

[1] Department of Information Systems and Computing, Regional University of Blumenau. Rua Antônio da Veiga 140, 89030-903 Blumenau, Brazil; (email: aureliof@furb.br; asartori@furb.br)
[2] COPELABS, Lusófona University of Humanities and Technologies. Campo Grande 376, 1749-024 Lisboa, Portugal; (email: valderi@ipportalegre.pt)
[3] VALORIZA, Research Center for Endogenous Resources Valorization. Instituto Politécnico de Portalegre, 7300-555 Portalegre, Portugal
* Correspondence: gsjesus@furb.br

**Abstract:** This paper presents the development and implementation of a machine learning model to estimate the future price of commodities in the Brazilian market from technical analysis indicators. For this, two databases were obtained regarding the commodities sugar, cotton, corn, soybean and wheat, which were submitted to the steps of data cleaning, pre-processing and subdivision. From the pre-processed data, recurrent neural networks of the long short-term memory type were used to perform the prediction of data in the interval of 1 and 3 days ahead. These models were evaluated using mean squared error, obtaining an accuracy between 0.00010 and 0.00037 on the test data for 1 day ahead and 0.00015 to 0.00041 for 3 days ahead. However, based on the results obtained, it can be stated that the developed model obtained a good prediction performance for all commodities evaluated.

**Keywords:** Commodities; Long Short-Term Memory; Machine Learning; Neural Networks; Prediction; Technical analysis.

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## 1. Introduction

Commodities are goods produced on a large scale, and one of its main features is the fact that they are stocked without losing quality, for example, oil, coffee, soybeans and gold. Such commodities can be traded on the futures market, through futures contracts, which represent agreements to buy and sell for a certain price and period, similar to the stock market [1]. There are two classes of traders, traders in commodity futures markets: hedgers and speculators. Hedgers, who are usually producers, seek to hedge their future physical position in a commodity by selling futures contracts. Speculators, seeking speculative profits, take the buy side of these trades. Consequently, making accurate commodity price predictions can benefit both classes of traders by leveraging their economic potential, which in turn can indirectly bring benefits to the general population.

For Kim [2], it is commonly accepted that there is an inverse relationship between commodity prices such as oil, wheat, base metals, etc. and the economy: when commodity prices fall, the economic effects are positive. Fang *et at.* [3] points out that agricultural commodity price prediction is an essential task for a nation's political-economic landscape to emerge. Improving the accuracy of forecasting the future prices of agricultural commodities is important for investors, agricultural producers, and policy makers. This avoids risks and allows government departments to formulate appropriate agricultural regulations and policies.

Currently, there are several scientific researches that investigate the predictability of the commodity market as well as the stock market. Among them, one can highlight the studies of Rigatos *et al.* [4] who proposed a method to predict commodity prices using partial differential equation and Kalman filtering. Borovkova and Tsiamas [5] applied an LSTM neural network for stock forecasting. Yin and Yang [6] investigated the usability of technical indicators to directly forecast oil prices by comparing their performance with macroeconomic variables. They point out that technical indicators have superior prediction than macroeconomic variables, being substantial during recessions and expansions, and can effectively detect typical declines in oil returns near the peaks of business cycles.

Given these circumstances, this work presents the development and implementation of a machine learning model that uses historical series of international and national prices, as well as their respective indicators of technical analysis to estimate the future price of commodities within the Brazilian market, going through the stages of analysis of the technical indicators most susceptible to the problem, development of a model of data prediction for the international market and another for the national market of commodities and, efficiency evaluation, generating finally, a computational artifact.

This work is relevant because it will help the scientific community by presenting a study using machine learning algorithms in combination with technical analysis for the prediction of short-term time series, using data from foreign markets to predict national data. Finally, its relevance for investors, farmers, and members of government departments is highlighted, since with an accurate commodity price prediction it is possible to make good buying and selling decisions, thus leveraging the economic potential of the individual, company, or country.

## 2. Related Works

Commodities have always been a part of our daily lives and are now also considered an important asset class on the financial markets. Most commodities, including gold, oil, natural gas, etc., are now traded by futures contracts on stock exchanges [7]. The authors also point out that a futures forward contract between a buyer and a seller is an agreement in which the seller needs to deliver a specified quantity of commodity to the buyer at a future date at the previously agreed price.

According to Kent, Filbeck and Harris [8], another way to invest in commodities is to buy shares in companies whose main business model depends on different commodities and various physical market sectors. In this case, the return depends not only on the commodities, but also on the performance of the stock market. Kent, Filbeck and Harris [8] also suggest the Exchange-Traded Fund (ETF) as a form of investment. Commodity ETFs are investment vehicles for investors and traders who need to hedge risk or want to gain exposure to physical commodities, such as agricultural products, energy resources, and metals. Such contracts represent the commodity and track the performance of a specific precious commodity.

Carrara and Barros [9] in turn, evaluated how shocks from commodity prices, have impacted Brazilian inflation and how and how effectively the country's monetary policy has responded. According to the authors, the inflation rate is influenced by the expectations that the market forms about it and then by the behavior of supply-side prices. Deviations of inflation from expectations are attributable to unanticipated variations in supply shocks (exchange rate and commodities) and the output gap. Chisari, Mastronardi, and Romero [10], on the other hand, when studying the vulnerability of three Latin American economies (Argentina, Chile, and Brazil), report that Brazil would be the least affected by drops in commodity prices because its economy is more diversified and the manufacturing sector could benefit from lower prices of imported inputs. However, they point out that the increase in the prices of imported commodities could have a negative impact on the country's economy.

Charles Dow, editor of The Wall Street Journal at the end of the 19th century, published several articles on the stock market. His theories boil down to six principles and are known to this day as the basis of technical analysis, these being (i) prices discount everything, (ii) the market has three trends, (iii) the primary trend has three phases, (iv) volume must confirm the trend, (v) the trend needs to be confirmed by two indices, and (vi) a trend is valid until the market indicates a definite sign of reversal [11].

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Given these principles, Martins [12] defines technical analysis as a way to study the past quotations of an asset. With it, one must find patterns and apply them to the future, creating performance forecasts such as price and duration of operations. Still, according to Martins [12], for the analysis to be done, it is necessary to divide the quotes into predetermined periods, such as days, weeks or months. It is also very common to use much shorter periods of minutes, such as one minute, two minutes and so on, usually up to a maximum of one hundred and twenty minutes.

Abe [11] also describes some basic principles of technical analysis, its concepts, characteristics, analysis patterns, tools and strategies, an explanation of capital management and operations organization. As indicators, the author cites moving averages, which are lines drawn within a price chart that move whenever a new price is entered into the chart, the Converging and Diverging Moving Average (CDM) which shows the difference between two Exponential Moving Averages (EMA), one fast (usually twelve periods) and one slow (usually twenty-six periods), and the Relative Strength Index (RSI), which measures how many days within a predetermined period were bullish and how many were bearish, showing the result on a scale of 0 to 100%.

On the other hand, Martins [12] categorized as basic indicators the moving averages, the relative strength index and the Fibonacci sequence for the creation of support and resistance lines. According to the author, they are used to make buying and selling decisions, where the price should fall to find support or rise until it finds resistance. Geometric figures can be drawn on a chart from the uptrend and downtrend lines, along with horizontal support and resistance lines. Such figures identify buy and sell points with target price projections and their most likely duration, among them, the triangle, the Flag or Flamula, the Rectangle, the Shoulder-Over-Head (OCO) and the Inverted Shoulder-Over-Head (OCOI) were cited.

As advanced indicators, Martins [12] categorized the (i) Needles - Didi Index, which indicate when prices should rise or fall rapidly; (ii) Bollinger Bands, which are the visual demonstration of the average and standard deviation of the prices of an asset within its own chart, the gaps that are empty intervals between the prices of the candles, i.e., price levels where there was no business; (iii) Reversal Islands, which occur when two gaps, one up and one down, occur in the same price range, separating the chart into two areas; (iv) Directional Movement, which defines the current trend of an asset, in addition to issuing buy and sell signals and predicting reversals; (v) Stochastic whose shows the value of the last closing price in relation to the maximum-minimum range of the analyzed period and the (vi) Parabolic Stop and Reverse (SAR) which is a trading system which is based on the premise that the investor will always be positioned in the market.

Silva [13] indicates that, nowadays, the financial success of rural activities depends heavily on the success in the commercialization of agricultural commodities. According to the author, the increase in agricultural production costs observed in recent years, associated with the stagnation of productivity of the main agricultural commodities have forced farmers to make an increasingly efficient planning of the marketing of production, making it necessary to understand the different mechanisms of marketing of agricultural commodities available and draw strategies to protect themselves from market fluctuations and to ensure greater profitability of agricultural activity.

### *2.1. Time series forecasting*

In the context of time series, there are various scenarios and applications that demand data management and communications between different devices, users and data in general. There are several solutions that address data management based on privacy [14] and information security rules [15], including decentralized implementation [16], smart environments [17,18], disruptive technologies [19], and vulnerability prediction [20].

There are several approaches that can be used successfully to time series forecasting, such as ensemble learning models [21], which combine weak learners to generate a model with greater predictive capability. Ensemble models can be combined in different ways,

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generating a wide range of possibilities, such as bagging [22], boosting [23], random subspace, stacked generalization [24], among others. Classical models can also be employed in this context, like those based on neuro-fuzzy systems [25,26], group method of data handling [27], and multilayer Perceptron [28]. In addition to prediction these approaches can be used for classification [29], through shallow layer structures [30–32] or deep learning strategies [33,34].

In scenarios that address the use of artificial intelligence mostly make use of devices and communications involving protocols and algorithms focused on the internet of things [35–37]. These applications extend to urban search and rescue [38], classifying garments [39], resource planning [40], industrial applications [41–43], communications [44,45], electrical power system [46,47], sustainability [48], fault analysis [49–52], and demand forecasting [53]. To build a learning system, it is necessary to define the task to be performed, the performance measure, and the training experience [54]. The type of knowledge to be learned must be extracted, have a representation of that knowledge, and a learning mechanism. Mitchell [55] points out that a performance measure often used in regression models is the mean squared error (MSE), which consists of the average of the squared prediction errors over all instances of the data set, in which the prediction error is the difference between the true value and the predicted value for an instance.

Goodfellow, Bengio, and Courville [56] point to three categories of intelligent algorithms for building learning systems. In the first, are the rule-based systems, in which from an input, a procedural processing is performed, generating an output. In the second are the classical machine learning algorithms, in which, starting from an input, manual processing of the features is performed and a mapping is produced from them, and upon completion of the mapping, the output is generated. Finally, there are the representation models, these process the features from learning the data, map the features and produce the output. The authors also add a subcategory to representation models, which besides containing all the features of a representation model, have a mechanism where more abstract features are extracted from additional layers inserted into the algorithm.

Neural networks that use the long short-term memory (LSTM) cell architecture have mechanisms that allow the neural network to accumulate information over a long duration of time [57–59]. According to Goodfellow, Bengio, and Courville [56], these neural networks have cells that are recurrently connected to each other and their input values can be accumulated in a state unit, which has its own linear loop, with weight controlled by the forget gate. Goodfellow, Bengio, and Courville [56] also point out that the output of the cell can be turned off by the output gate and that all the gate units have sigmoid nonlinearity, while the input unit can have any nonlinear compression function. The state unit can also be used as an extra input for the other gating units [60].

Srivastava *et al.* [61] indicates that with limited training data, many complex relationships between inputs and outputs can result from sampling noise, existing in the training set but not in the test set, which consequently generates the problem of overfitting, in which the neural network generalizes the training set but fails to make predictions for the test data. To solve such a problem, they proposed a technique called dropout, which in addition to significantly reducing overfitting, provides a way to combine different neural network architectures. It consists of temporarily disconnecting neural network units in the training phase, along with all their input and output connections, in a random manner, with a predefined probability of disconnection. In the testing phase the units are always present, but the weights are multiplied by the defined probability.

Neural nets can have their training stage optimized [62]. The Adam algorithm from Kingma and Ba [63], which is derived from deadaptive moment estimation (DME), can be used to replace the classic stochastic gradient descent (SGD) to iteratively update the network weights. This algorithm uses a learning rate for each weight in the net and adapts separately while training occurs. Its main advantages, are that it is computationally efficient, appropriate for problems with sparse or noisy gradients, well suited for problems with a large number of data or parameters, and finally, low memory cost.

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Deep layer-based models are increasingly being used for time series forecasting [64,65], especially the LSTM model for its ability to handle nonlinearities [66]. The combination with noise reduction techniques can considerably improve the ability of forecasting models [67]. When noise reduction techniques such as the wavelet transform are combined with high performance models such as LSTM superior prediction results can be obtained [68].

## 3. Method

This chapter describes the most relevant aspects related to the application development, presenting the functional requirements (FR) and the non-functional requirements (NFR) in Table 6. It also presents details about the implementation, including the description of the data, the pre-processing performed, the neural network architectures used, and the steps followed in the development of the application.

**Table 1.** Requirements.

| Specification | Code | Functional Requirements. |
|---|---|---|
| Functional | RF01 | Allow loading of commodity data from an international financial market and a national market. |
| | RF02 | Process technical indicators referring to commodities financial data. |
| | RF03 | Predict the price of selected commodities in a 1- and 3-day ahead perspective. |
| | RF04 | Display model performance via mean squared error. |
| | RF05 | Display model performance, actual and predicted prices in a dashboard. |
| Non-Functional | RNF01 | Be developed using the Python programming language. |
| | RNF02 | Use the Pandas and Scikit-learn libraries for data pre-processing. |
| | RNF03 | Use the Keras library for model development and training |
| | RNF04 | Use the Jupyter Notebook platform to display the results. |
| | RNF05 | Use the TA-Lib library to calculate the technical indicators. |
| | RNF06 | Use the long short term memory neural network architecture to develop the predictive models. |

In the application, it was used the databases made available by (i) Yahoo Finance [69] international indicators and (ii) University Of São Paulo [70] national indicators, having financial information of five agricultural commodities, being them sugar, cotton, corn, soybean and wheat, with daily frequency in the interval from January 03, 2005 to December 31, 2019. The variables contained in the databases provided by (i) are the opening, maximum, minimum, closing, closing adjustment, and volume values, while the database provided by (ii) contains the price of the day in *reais* and in dollars, in which the values in *reais* were selected for this project. Table 2 presents the relation between the databases, indicating their respective codes for obtaining.

To add information to the national database, predictor models were created for the international commodities market that used as input variables the maximum, minimum and volume values, as well as technical analysis indicators. Their predictions were incorporated into the national database.

From the TA-Lib technical analysis library, an open source library available for the programming languages C/C++, Java, Perl, Python and .NET which is widely used in software requiring technical analysis of financial market data, as it enables the calculation of technical analysis indicators in an automated manner [71]. Added to the database provided

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**Table 2.** Database Relationships.

| Commodity | Yahoo Finance [69] | Code University Of São Paulo [70] |
|---|---|---|
| Sugar | SB = F | CEPEAESALQ Crystal sugar indicator |
| Cotton | CT = F | Cotton lint indicator CEPEAESALQ - 8 days term |
| Corn | ZC = F | Corn Indicator ESALQBM&FBOVESPA |
| Soybeans | ZS = F | Soybean indicator CEPEAESALQ - Paraná |
| Wheat | KW = F | Average price of wheat CEPEAESALQ - Paraná |

by Yahoo Finance [69] were 3 volume indicators, 30 momentum indicators, 3 volatility indicators, and 7 cycle detectors, for a total of 43 technical indicators. Table 3 presents the calculated technical indicators, classifying them by their type.

**Table 3.** Database Relationships.

| Type | Calculated Indicators Yahoo Finance [69] |
|---|---|
| Cycle detectors | HT DCPERIOD, HT DCPHASE, INPHASE, QUADRATURE, SINE, LEADSINE, HT TRENDMODE |
| Momentum indicators | ADX, ADXR, APO, AROON, AROONOSC, BOP, CCI, CMO, DX, MACD, MACDEXT, MACDFIX, MIF, MINUS DI, MINUS DM, MOM, PLUS DI, PLUS DM, PPO, ROC, ROCP, ROCR, ROCR100, RSI, STOCH, STOCHF, STOCHRSI, TRIX, ULTOSC, WILLR |
| Volatility indicators | ATR, NATR, TRANGE |
| Volume indicators | AD, ADOSC, OBV |

Once the calculations of technical indicators were performed, the most relevant characteristics were selected for the data prediction of each commodity. For this, the Pearson correlation was calculated between each technical indicator with the closing data of the day. This correlation indicates the strength of the linear association between two variables

$$r = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}, \tag{1}$$

where $r$ is Pearson's correlation coefficient, $x_i$ the values of variable $x$ in a sample, $\bar{x}$ the mean of the values of variable $x$, $y_i$ the values of variable $y$, and $\bar{y}$ the mean of the values of variable $y$.

## 4. Results of Application

The indicators whose correlation module was higher than 0.15 were kept, since by using such a value, a considerable amount of technical indicators were kept, selecting those that stood out the most. Table 4 describes the coefficients found for five technical indicators referring to the closing market values of commodities for the database made available by Yahoo Finance [69]. With this, data cleaning was performed, which excluded the first few rows of the dataset that contained the null value due to preprocessing of the technical indicators.

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**Table 4.** Pearson correlation coefficient on international market data.

| Indicator / Commodity | Sugar | Cotton | Corn | Soybeans | Wheat |
|---|---|---|---|---|---|
| NATR | 0.31008719 | 0.35868731 | 0.31442310 | 0.28694566 | 0.11916946 |
| OBV | 0.45523242 | 0.16162160 | 0.23452564 | 0.30119409 | 0.59871290 |
| MINUS DM | 0.58859266 | 0.63013850 | 0.50869227 | 0.38265851 | 0.59956594 |
| TRANGE | 0.62805229 | 0.69649601 | 0.56482108 | 0.47438842 | 0.47674641 |
| PLUS DM | 0.73745874 | 0.83559670 | 0.67304095 | 0.61342416 | 0.75163947 |

Observing Table 4, one notices that the NATR indicator obtained a correlation index lower than 0.15 for the wheat commodity, and was excluded from the database. After selecting the technical indicators with correlation greater than 0.15 and performing the data cleaning, the data normalization technique was employed. This step defined a range of values for the data aiming to reduce the difference between the lowest and the highest value of the set.

$$y = \frac{(x - x_{min}) * (d_{max} - d_{min})}{x_{max} - x_{min}} + d_{min} \tag{2}$$

where, $y$ represents the normalized value, $x$ the value to be normalized, $x_{max}$ refers to the maximum value to be normalized, $x_{min}$ to the minimum value to be normalized, $d_{max}$ to the maximum desired value and $d_{min}$ to the minimum desired value. In this project, 1 (one) was used as the maximum desired value and 0 (zero) for the minimum desired value.

After the data normalization step, the set provided by Yahoo Finance [69] was divided into 20% for training and 80% for testing. With this, it became possible to build and train the predictive models for commodities within the international market. The architecture of these models consisted of an LSTM layer with 128 units and 20% dropout, followed by an LSTM layer with 256 units and 20% dropout. Another LSTM layer with 256 units, a fully connected layer (Dense) with 256 neurons and 20% dropout, a 128-unit LSTM layer, a 128-unit fully connected layer with 20% dropout. And finally a fully connected layer with one neuron and the rectified linear unit (ReLU) activation function [72]. This architecture can be visualized graphically in Figure 1.

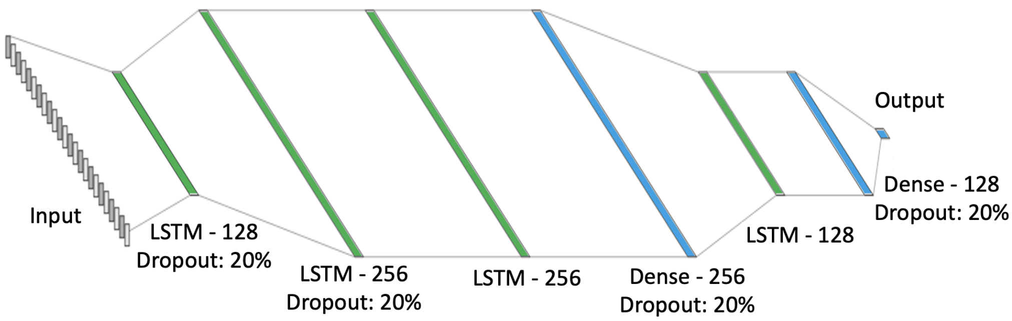


**Figure 1.** Proposed model for predictions at the international level.

Once the training stage was concluded, the predictor models for the international market were evaluated using as performance metric the mean squared error (MSE), whose results for all commodities used, with predictions for 1 and 3 days ahead are described in Table 5. Finally, such models were used to generate a database of international commodity market predictions on the test set.

The MSE indicates how close the values of two curves are, being zero the smallest possible value, which indicates total overlap, and one the maximum possible value, which indicates the worst overlap. It can be verified through Table 5 that for all commodities the MSE value was below 0.005, indicating that the prediction curves were close to the actual

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**Table 5.** MSE of the neural network models referring to the international market.

| Commodity | Training phase: 1 day ahead | Test phase: 1 day ahead | Training phase: 3 days ahead | Test phase: 3 days ahead |
|---|---|---|---|---|
| Sugar | 0.00040 | 0.00228 | 0.00073 | 0.00172 |
| Cotton | 0.00062 | 0.00011 | 0.00139 | 0.00022 |
| Corn | 0.00039 | 0.00062 | 0.00114 | 0.00118 |
| Soybeans | 0.00062 | 0.00113 | 0.00165 | 0.00308 |
| Wheat | 0.00048 | 0.00056 | 0.00108 | 0.00153 |

price curves, with cotton standing out, which obtained the lowest MSE values in the test phase, for both predictions of 1 and 3 days ahead.

To establish the indicators for the national market, similar processes were performed on the database made available by the University of São Paulo [70]. Figure **??** demonstrates the flow followed to make the predictions about the national commodity market. For the national market database, 13 moment indicators and 7 cycle detectors were added, totaling 20 technical indicators. The difference in the number of technical indicators was due to the number of characteristics made available by each database. Table 6 presents the technical indicators used, classifying them by type.

**Table 6.** Technical indicators calculated on the national database, classified by their type.

| Indicators | National (University Of São Paulo) [70] |
|---|---|
| Cycle Detectors | HT DCPERIOD, HT DCPHASE, INPHASE, QUADRATURE, SINE, LEADSINE, HT TRENDMODE |
| Moment Indicators | APO, CMO, MACD, MACDEXT, MACDFIX, MOM, PPO, ROC, ROCP, ROCR100, RSI, STOCHRSI, TRIX |
| Volatility Indicators | Not applicable |
| Volume Indicators | Not applicable |

These indicators also underwent the selection process, using Pearson's coefficient as a criterion. Table 7 shows the correlation coefficients for 5 technical indicators referring to the database made available by the University of São Paulo [70].

**Table 7.** Pearson's correlation coefficient on the national market data.

| Indicator / Commodity | Sugar | Cotton | Corn | Soybeans | Wheat |
|---|---|---|---|---|---|
| RSI | 0.18509653 | 0.08100763 | 0.30984300 | 0.30517003 | 0.16748187 |
| APO | 0.19549568 | 0.16702112 | 0.26767576 | 0.28277952 | 0.23069744 |
| MACDFIX | 0.26530357 | 0.21047608 | 0.34258186 | 0.38902278 | 0.31027552 |
| HT DCPERIOD | 0.27262300 | 0.10624508 | 0.27997955 | 0.25604055 | 0.02854838 |
| TRIX | 0.43366235 | 0.21416214 | 0.46843084 | 0.54283840 | 0.47789509 |

From Table 7, it can be seen that the correlation values for the technical indicators RSI, for the commodity cotton and HT DCPERIOD, for the commodities cotton and wheat did not reach an index greater than 0.15, being excluded from the national database for the respective commodities. Finally, these data also went through the normalization process, being scaled to the closed interval of 0 to 1.

With the data from the University of São Paulo [70] normalized, they were paired with the predicted data for the international commodities market. With this, the input set was formed for the predictive models for the national market. These data in turn were again normalized between 0 and 1, for the adjustment of the predictions, and finally, were subdivided into two sets, being 80% of the data for training and 20% for testing.

From this, the predictive models for the national commodities market were created, composed of an LSTM layer with 128 units and dropout of 20%, followed by an LSTM layer with 256 units, a fully connected layer with 256 neurons and dropout of 20%, an LSTM

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layer of 128 units, a fully connected layer of 128 units with dropout of 20% and finally, a fully connected layer with one neuron and ReLU activation function. The described model can be visualized graphically in Figure 2.

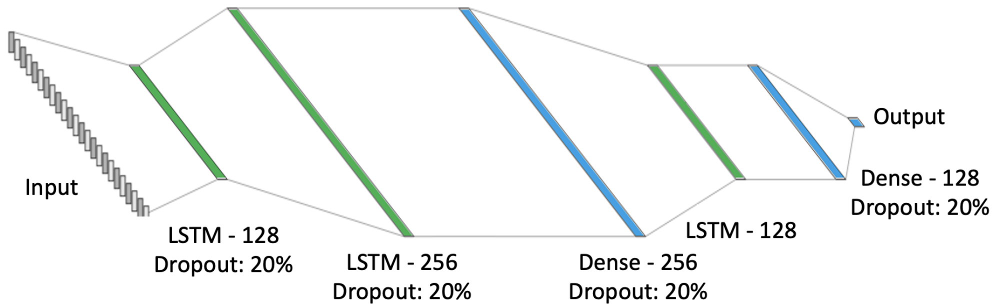


**Figure 2.** Proposed model for nationwide predictions.

This model in turn also underwent the evaluation process, using as performance metric the MSE, whose results for all commodities used, with predictions for 1 and 3 days ahead can be found in Table 8. With this, it was possible to make the predictions for the national commodities market, fulfilling the proposed objective.

**Table 8.** MSE of the neural network models referring to the national market.

| Commodity | Training phase: 1 day ahead | Test phase: 1 day ahead | Training phase: 3 days ahead | Test phase: 3 days ahead |
|---|---|---|---|---|
| Sugar | 0.00038 | 0. 00019 | 0.00027 | 0.00017 |
| Cotton | 0.00023 | 0. 00010 | 0.00025 | 0.00015 |
| Corn | 0.00082 | 0. 00027 | 0.00030 | 0.00030 |
| Soybeans | 0.00047 | 0. 00037 | 0.00045 | 0.00042 |
| Wheat | 0.00028 | 0. 00016 | 0.00021 | 0.00017 |

From the results described in Tables 7 and 8, the high predictive power of the models developed is remarkable, with emphasis on the cotton commodity, which obtained the lowest MSE values for both predictions referring to the test data. Figure 3 shows the graphs of the predictions found by the neural network models at the international level in comparison with the actual data in the test set, and Figure 4 shows the graphs of the predictions found by the models at the national level, in comparison with the actual values, again in the test set.

In Figure 3 it can be observed that, despite the model having achieved good predictions, in some situations the predictions curve shifts in relation to the actual data, especially for the soybean commodity, which presented the worst predictions for 3 days ahead. This situation confirms the evaluation obtained by the MSE performance metric, in which soybean presented the worst result, with a value of 0.0308 for 3-day ahead predictions.

It is noteworthy that for the international market data, only 20% of the data set was used for training, which may have influenced such deviations in the prediction curve. On the other hand, in Figure 4 the prediction curves have a small displacement in relation to the real data, again confirming the data presented by the performance metric and indicating that the methodology presented in this work is appropriate to perform the prediction of agricultural commodities.

## 5. Conclusion

The forecasting of agricultural commodity prices is an important economic task and impacts several social classes, being directly or indirectly affected. Aiming to obtain accurate predictions in this area, this paper presented an approach for the prediction of future prices of agricultural commodities using technical analysis and machine learning indicators.

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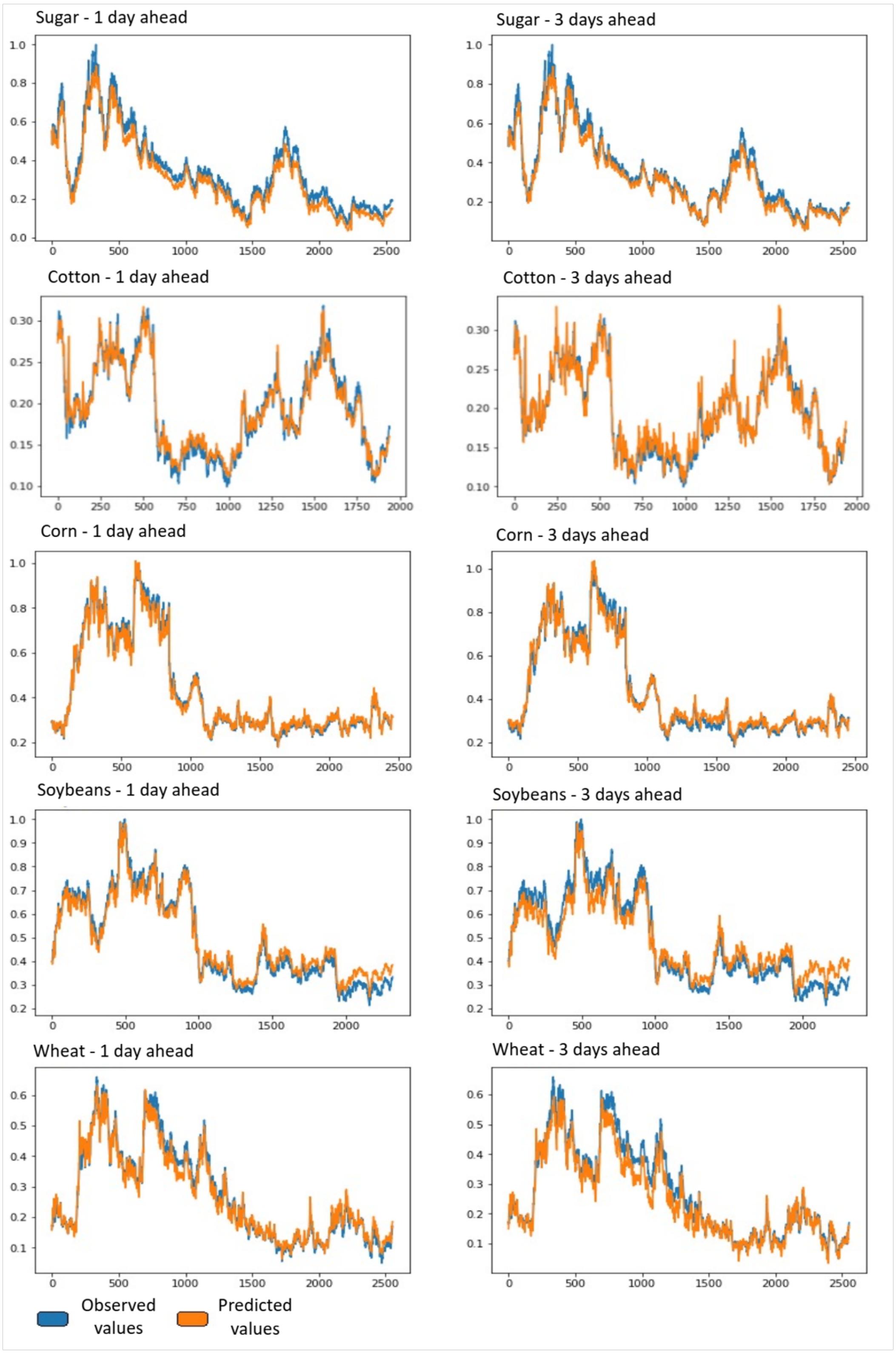


**Figure 3.** Model predictions at the international level.

For this purpose, two databases were used, which contained financial information about the commodities sugar, cotton, corn, soybeans, and wheat, with daily frequency data from January 3, 2005 to December 31, 2019. These databases went through the processes of cleaning, pre-processing, and subdividing the data to be used for training and evaluating the

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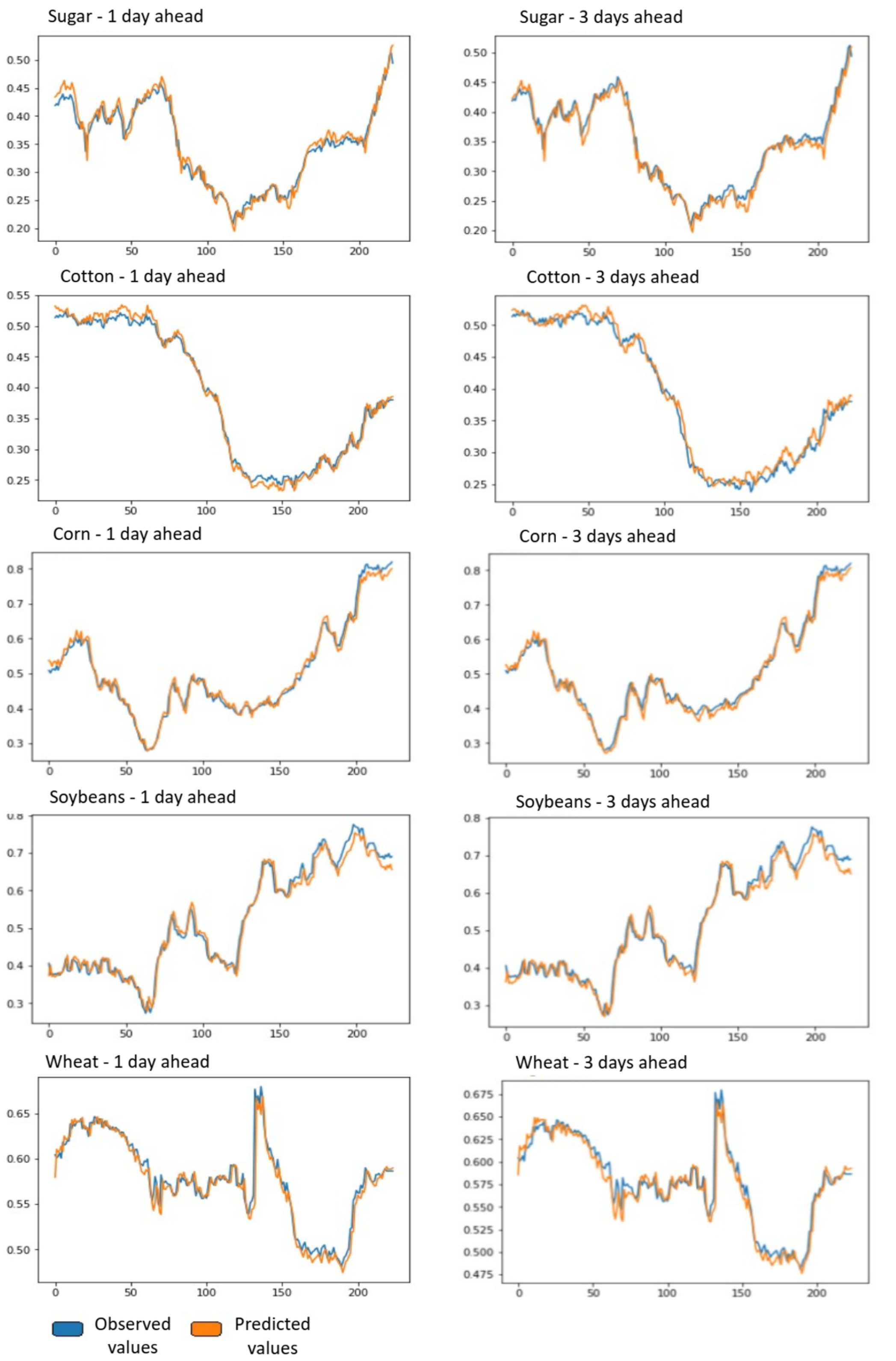


**Figure 4.** Model predictions at the national level.

models developed. The project was developed using Python programming language, using the libraries Pandas and Scikit-learn for data preprocessing, TA-Lib for the calculation of technical indicators, Keras for model development and training, and the Jupyter Notebook platform to display the results. These technologies proved to be effective, fulfilling their purpose.

During the course of the project, 43 technical indicators were added to the international database. In the national database, 20 technical indicators were added. These indicators went through a selective process, which kept in the databases those whose Pearson correlation module was greater than 0.15 in relation to the market closing data. With this, the data were normalized, being scaled to the closed interval from 0 to 1. Once these processes were completed, the international database was divided into 20% for training and 80% for testing. This database was then used to train the predictive models for the international commodities market. These models in turn generated predictions for the test data, and were coupled to the database of national commodities. From this, the national database was normalized again, and then divided into 80% for training and 20% for testing. Finally, the predictive models were created for this database, which obtained results between 0.00010 and 0.00037 RSM in the test data for 1 day ahead and 0.00015 to 0.00041 RSM in the test data for 3 days ahead, indicating a good prediction performance for all commodities evaluated, concluding the project's objective.

Regarding related work, this project presented an approach which unified technical analysis, the subject of study by Wang, Liu, and Wu [73], with machine learning algorithms, the subject of study by Zhang *et al.* [74] and Fang *et al.* [3]. In addition, this project stood out for the use of neural networks with LSTM architecture and the use of predictions on data from international markets to make predictions within the domestic commodity market. Also in relation to related works, it is noteworthy that only the work of Wang, Liu, and Wu [73] made use of technical indicators, which did not perform short-term predictions. Thus, it can be inferred that this work contributed to the literature by presenting a study that used machine learning algorithms in combination with technical analysis indicators for the prediction of short-term time series, making use of data from international and domestic markets for the prediction of commodity prices within the Brazilian market.

Finally, it is emphasized that this work was limited to only five commodities, however, it is suggested as extensions: (i) the use of this approach to predict non-agricultural commodities, such as gold and oil, (ii) the use and improvement of the methodology developed for predictions in different time intervals, with frequency higher and lower than that presented in this work, (iii) the improvement of the models developed through the insertion of other machine learning techniques and (iv) the development of a software that uses the proposed approach to make predictions about the future market of commodities.

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