Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Development of a Mobile Application with Machine Learning Models for the Early Identification of Diseases in the Banana Plant and to Promote Sustainable Agriculture

Ronald Winther Chasipanta Baraja, Darling Alexander Untuña Rosao, Cristian Darwin Borja Borja

Universidad Técnica de Cotopaxi, La Maná-Ecuador
Email: ronald.chasipanta3834@utc.edu.ec

Machine learning models in recent years have evolved through their complex algorithms, allowing process innovation, such as managing crop diseases. The following study offers the implementation of a mobile application with a machine learning model for disease detection, allowing the detection of phytosanitary diseases in the Bananera Luz Divina 4 in the canton of Quevedo. The Mobile-D methodology for planning and developing the application was necessary to optimise the tasks in implementing the functionalities and the mixed research approaches: documentary, experimental and analytical, and the development and training of the machine learning model. The development of a machine learning model trained with a dataset of images of diseases such as Moko, bacteriosis, black sigatoka, and Panama disease. Google Colab and the TensorFlow and Keras libraries were used to train and optimise the model using the adjustment parameters. The results show high accuracy in disease detection, offering growers an optimal and effective technological tool for productivity, mitigating economic losses and improving banana crop management. This implementation highlights the importance of integrating advanced technologies for plant health.

Keywords: Machine learning, plant diseases, artificial intelligence, Mobile-d methodology, tensorflow.

1. Introduction

Ecuador, one of the banana-producing countries in Latin America, according to (Serrano et al., 2020), "the income generated covers a significant percentage of the Gross Domestic Product, creating sources of employment and economic significance of the primary sector". Bananas are the most imported and, therefore, the most important product for the country's economy. Here, the importance of delivering a quality product is verifying that the product is in optimal conditions for the market. Farmers must monitor crops for diseases that can cause significant economic loss if not controlled in time.

Information systems and artificial intelligence have revolutionised how challenges in the agricultural sector are addressed; computational capacity and data availability have made it possible to develop increasingly sophisticated solutions. The agricultural sector has undergone a significant transformation by implementing technologies, enabling it to optimise processes and make decisions based on real-time data. Machine learning, the models created from advanced algorithms, has proven to be a powerful tool for detecting crop disease diagnostics. Systems based on artificial intelligence process a large amount of visual information and complex patterns that, in many cases, are imperceptible to the human eye, allowing the identification of phytosanitary problems in the early stages of banana development.

This article aims to demonstrate the results obtained using the trained model for detecting diseases in banana crops through the analysis with mobile devices (smartphone) previously implemented in an application. Based on the research, the following questions are posed: How much data is required to create an optimal model for the detection of the proposed diseases and the optimal detection of diseases using the application?

In recent years, banana production has shown significant fluctuations, with an overall downward trend, including a notable 15% decline between 2012 and 2019. This decline responds to several factors, including phytosanitary problems such as black Sigatoka, adverse climatic events -floods, strong winds and temperature variations- and competition from other producing countries in Central America. However, Ecuador has managed to maintain its competitive position thanks to comparative advantages such as its geographic location, optimal soil and climate conditions, efficient logistics infrastructure, and a well-established export sector. In the future, new challenges will require innovations in agricultural technology to deal with pests, increase productivity and meet the environmental demands of international markets (Sánchez et al., 2024).

Banana is a very popular fruit in human food, being produced in more than 135 countries, such as India with 30 million tons (Mtn), China (11 Mtn), Indonesia (7 Mtn), Brazil (6.8 Mtn), Ecuador (6.5 Mtn) and the Philippines (6 Mtn) (Aguilar-Anccota, Ruiz, et al., 2021). Banana is an important export product facing international competition, environmental sustainability and market diversification (Sanchez et al., 2024). Banana consumption is essential, according to Blasco and Gomez (2014) and Kumar et al. (2012); banana consumption facilitates the absorption of nutrients such as calcium, nitrogen and phosphorus, supporting tissue reconstruction. In addition, it is considered beneficial for people with intestinal disorders, such as ulcers, because it is one of the few fruits that can be consumed without risk. It also stands out as an excellent source of potassium (Martínez-Solórzano & Rey-Brina, 2021).

Historical facts demonstrate the trajectory of bananas in the country; these crops represent an important export item, generating foreign exchange and jobs for the country. They also have a long productive tradition in Ecuador, dating back to colonial times and the early twentieth-century banana boom. So, areas are specialised in their production (Sanchez et al., (2024)). Although bananas are important, some anomalies prevent consumption. Diseases in bananas are present, as stated in the research of Victor et al.: "The results showed fluctuations in the case of bananas with a downward trend, attributed to phytosanitary and climatic problems and external competition" (Sanchez et al., 2024).

Bacteriosis, caused by the genera Pectobacterium and Dickeya, which are characterised by their aggressiveness and production of symptoms through enzymatic degradation of the pectin of plant tissues, affecting the tissue firmness of the plants (Aguilar-Anccota, Ruiz, et al., 2021). Black Sigatoka (SN), caused by the fungus Pseudocercospora fijiensis, affects banana and plantain plantations worldwide and can lead to total crop loss (Adriano-Anaya et al., 2023). Panama disease is characterised by symptoms that begin in the lower or older leaves, which develop a generalised yellowing. As the disease progresses, leaf margins change from pale green to yellow, and necrotic streaks surrounded by a yellow border appear. Eventually, the leaves die, and the resulting clusters are usually small, with thin, underdeveloped fruit (Aguilar-Anccota, Arévalo-Quinde et al., 2021).

Mobile applications have become the primary means of communication in modern society. They stand out for their versatility and efficiency in providing reliable information at any time and keeping the user abreast of various topics (Acosta Espinoza et al., 2022). Mobile applications in society, not only in Ecuador but internationally in the last year, have allowed people to make use of this resource in a high percentage, mainly to learn about products and/or services provided by different institutions or organisations in order to acquire them or simply learn about them (Acosta Espinoza et al., 2022).

The development environment is necessary for implementing and creating the model, Google Colab, a free web platform that allows Jupyter notebooks to combine executable code with text, images, HTML and LaTeX. It is compatible with several Python libraries, such as Pandas, Numpy, Matplotlib, Keras and TensorFlow. It allows storing and accessing files through a Google Drive account, facilitating data analysis and visualisation (Gil-Vera & Quintero-López, 2021). Android Studio, a unified environment for mobile development, allows developers to create applications compatible with all Android devices from a single platform, optimising the development process and ensuring consistency across devices (Quisaguano et al., 2022).

The programming language is critical, allowing instructions to be created and the computer to understand it. Python is a high-level programming language with a simple syntax characterised by interpretation, making it particularly suitable for teaching and learning programming (Vidal-Silva et al., 2021). Dart programming language was created as a successor and replacement of JavaScript, integrating the main features of advanced standards (ES7), such as the "async" and "await" keywords. Unlike JavaScript, it presents a Java-like syntax to facilitate its adoption among developers of other languages (Quisaguano et al., 2022).

Frameworks and libraries are undoubtedly conducive to allowing existing code to create new applications. Flutter, a framework par excellence designed for interaction with Dart, optimises the syntax used by its root language. It has the best execution time among the frameworks offered on the market and integrates multiple free tools that are easy and light to debug the code (Quisaguano et al., 2022).

The TensorFlow tool is a machine learning system designed to operate in large and diverse environments, using data flow diagrams representing shared computations and states. Its structure allows the use of multiple devices, such as CPUs, GPUs and specialised processing units for tensors, which facilitates training and inference in deep neural networks (Punguil, 2023). On the other hand, Keras, an algorithm integrated in TensorFlow, facilitates model training, allowing to accurately classify various categories and subcategories, such as lines and sublines of research, by collaborating with tools such as NLTK and SKLearn (Punguil, 2023). To display model results, matplotlib, a standard and widely used Python graphics library, is ideal for producing high-quality graphics suitable for both print and digital publications. It allows the generation of various visualisations, including time series, histograms, power spectra, bar charts and error plots (Vilca Paredes, 2020). The implementation of the model on smartphones with liteRT, formerly called TensorFlow Lite, is a set of tools that makes it easy for developers to implement their machine learning models on mobile, IoT devices and more.

Artificial intelligence is a tool that, in recent years, has been constantly evolving: the best known today is the one created by OpenAI with its GPT model. It took time for this multipurpose model to be trained to be what it is now. There is no doubt that artificial intelligence will change our vision for the future, optimise processes, and improve our lifestyles by using it as a working tool. Artificial intelligence groups diverse techniques that improve computer systems to perform tasks such as classification, optimisation, prediction and pattern recognition, functions commonly associated with human capabilities (Torres Solís & Quiroz Juárez, 2023).

Torres Solís and Quiroz Juárez (2023) mention that machine learning is a branch of artificial intelligence that creates computer systems capable of learning from data collection through algorithms. This allows the explicit programming of the parts—which, coupled, help to solve a problem—to be replaced with algorithms capable of finding the solution autonomously. This suggests that the quality and size of the data set are significant aspects that influence the performance of the algorithms.

On the other hand, Torres Solís & Quiroz Juárez (2023) describe that supervised learning seeks to adjust the model's parameters to reproduce an output as close as possible to the desired or known one. This objective is achieved by entering labelled examples and minimising the error produced between the output estimated by the model and the "correct" output. Likewise, unsupervised learning is a method that enables the grouping of data sets according to similarities and patterns in common without the need to have prior information on labels or structures. Finally, reinforcement learning uses a reward and penalty scheme, where the agent (model to be trained) starts from a given initial state and executes an action that leads to an interaction with the environment.

Deep learning is a set of algorithms that resemble the human brain in obtaining results. These algorithms follow the processes logically, simulating their operation as neurons would. Deep learning is a subset of machine learning that automates obtaining features and concentrates models with many adjustable parameters (Torres Solís & Quiroz Juárez, 2023).

Artificial neural networks constitute an interconnected group of artificial neurons arranged in layers (input, hidden, and output), which transmit signals to their adjacent neurons (Torres Solís & Quiroz Juárez, 2023). Convolutional neural networks are a deep learning architecture comprising several layers, such as clustering, convolution, dropout, and interconnected layers with different tasks (Aroca et al., 2023).

2. METHODOLOGY

Based on the literature information search in articles in academic databases such as Scielo, research on the impact of banana diseases and how they affect farmers' economies, the search strategy for training a machine learning model, platforms and services for training the model, and the development environment for the mobile application for implementing the model.

Mobile-D is an agile methodology for mobile application development. The initial phase involves exploration and research with experts in the field and collecting information for processing in the model's training. The importance of the documentary review in collecting information from different scientific and agricultural sources, planning for the development of the model and application is planned based on the collection of experimental data, establishing a foundation for innovative development. The Mobile-D methodology provides Sprints with a focus on each stage of development, structured in dynamic phases of exploration, initialisation, production, stabilisation, and testing.

The model's training is based on a dataset of 1,000 photos of the different diseases. Seventy per cent were assigned for training, 20 per cent for validation, and 10 per cent for testing. As in Figure 1, each disease is assigned to a class for recognition.

```
[ ]  !unzip DATASET.zip
```

```
[ ]  import tensorflow as tf
     import matplotlib.pyplot as plt
```

```
[ ]  img_height, img_width = 256, 256
     batch_size = 20
     EPOCHS = 40

     train_ds = tf.keras.utils.image_dataset_from_directory(
         "DATASET/train",
         image_size = (img_height, img_width),
         batch_size = batch_size
     )
     val_ds = tf.keras.utils.image_dataset_from_directory(
         "DATASET/validation",
         image_size = (img_height, img_width),
         batch_size = batch_size
     )
     test_ds = tf.keras.utils.image_dataset_from_directory(
         "DATASET/test",
         image_size = (img_height, img_width),
         batch_size = batch_size
     )
```

Fig 1. Dataset import directory assignment is for training, validation, and testing.

A list is created with the values for classifying the images; this allows assigning the class name to each disease to be trained, which identifies the model by analysing an image of the disease to be detected (Figure 2).

```
[ ]  class_names = ["HOJAS SANAS",
                    "MAL DE PANAMÁ",
                    "PUDRICIÓN HÚMEDA BACTERIANA",
                    "SIGATOKA NEGRA"]
```

Fig 2. List of disease names.

The neural network model comprises pixel-scale normalisation, the convolutional "conv2d", clustering "maxpooling2d" layers, where these extract important features from the images, the "dense" layer that converts the features into a plane vector and the dense "dense" layers, as seen in Fig 3, are defined.

```
[ ]  model = tf.keras.Sequential(
         [
          tf.keras.layers.Rescaling(1./255),
          tf.keras.layers.Conv2D(32, 3, activation="relu"),
          tf.keras.layers.MaxPooling2D(),
          tf.keras.layers.Conv2D(32, 3, activation="relu"),
          tf.keras.layers.MaxPooling2D(),
          tf.keras.layers.Conv2D(32, 3, activation="relu"),
          tf.keras.layers.MaxPooling2D(),
          tf.keras.layers.Flatten(),
          tf.keras.layers.Dense(128, activation="relu"),
          tf.keras.layers.Dense(4)
         ]
     )
```

Fig 3. Model architecture, parameter assignment.

Model configuration making use of the "Adam" algorithm, activation of the loss function for multiclass classification and accuracy of the metric in accuracy, as shown in Fig 4.

```
[ ]  model.compile(
         optimizer="adam",
         loss=tf.losses.SparseCategoricalCrossentropy(from_logits = True),
         metrics=['accuracy']
     )
```

Fig 4. Model compilation, algorithm assignment and fitting.

The training of the model, the fit method, is a deep learning model. Parameters are assigned for training and validation, and the number of times the model will iterate on each data set is shown in Figure 5.

```
[ ]  model.fit(
         train_ds,
         validation_data = val_ds,
         epochs = 40
     )
```

Fig 5. Training the model with the training and validation data.

The first image is selected from the test dataset set. The selected and converted image is converted to use the model and displayed as a result. When the conversion is complete, the actual image and the class identified by the model are displayed, as in Figure 6.

```
[ ] import numpy as np
    for images_batch, labels_batch in test_ds.take(1):

        first_image = images_batch[0].numpy().astype('uint8')
        first_label = labels_batch[0].numpy()

        print("Primera imagen a predecir")
        plt.imshow(first_image)
        print("Clase correcta:",class_names[first_label])

        batch_prediction = model.predict(images_batch)
        print("Clase predicha:",class_names[np.argmax(batch_prediction[0])])
```

```
Primera imagen a predecir
Clase correcta: HOJAS SANAS
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 685ms/step
Clase predicha: HOJAS SANAS
```

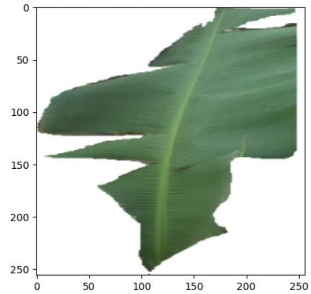

Fig 6.Evaluation and prediction.

Exporting the model to LiteRT, formerly called TensorFlow Lite, to be implemented on mobile devices with lower computational resources, it is ideal to use this type of format, Figure 7.

```
[ ] converter = tf.lite.TFLiteConverter.from_keras_model(model)
    tflite_model = converter.convert()

    with open("model.tflite", 'wb') as f:
      f.write(tflite_model)
```

Fig 7. Conversion of the model to LiteRT.

3. RESULTS AND DISCUSSION

The results obtained in training the model using the confusion matrix to evaluate the classification performance demonstrate positive values in disease arrest. Based on the confusion matrix, there was a high bacteriosis arrest followed by the identification of Black Sigatoka, as visualised in Figure 8.

```
[ ] import numpy as np
    from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
    import matplotlib.pyplot as plt

    true_labels = []
    predicted_labels = []

    for images_batch, labels_batch in test_ds:
        predictions = model.predict(images_batch)
        predicted_labels.extend(np.argmax(predictions, axis=1))
        true_labels.extend(labels_batch.numpy())

    true_labels = np.array(true_labels)
    predicted_labels = np.array(predicted_labels)
```

```
[ ] conf_matrix = confusion_matrix(true_labels, predicted_labels)

    disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=class_names)
    disp.plot(cmap=plt.cm.Blues, xticks_rotation='vertical')
    plt.show()
```

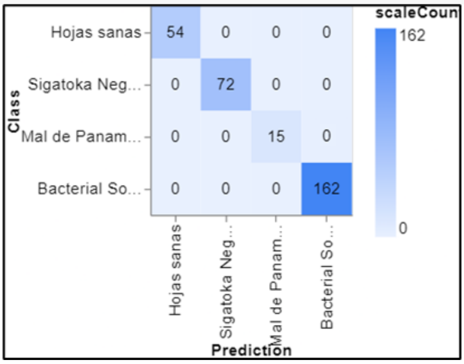

Fig 8. Confusion matrix, model performance.

The model's training for detecting banana diseases: Panama disease, bacterial wet rot (bacteriosis) and black Sigatoka. The optimised model can identify the aforementioned diseases; implementing the model with the mobile application was vital for managing and controlling diseases of the Luz Divina 4 banana plantation. The results indicate this by analysing the diseases analysed in banana plants. The model was optimised for an application that uses the mobile device's resources, analyses the images captured with the device, and can be used offline without needing an Internet connection, Figure 9.

Fig 9. Use of the model in the application.

The analyses performed demonstrate an acceptable effectiveness in identifying banana diseases. They show the percentage of cases in which evidence of the disease was found; the disease with the highest percentage stands out.

The model created for classifying images into four categories has addressed the problem of identifying diseases affecting bananas, allowing the management and treatment of the diseases they present, and providing a technological tool to farmers. On the other hand, the deep learning model called YOLO should be considered for adding new features such as real-time detection. YOLO, short for "You Only Look Once," is a leading object detection algorithm that excels in real-time identification and recognition of multiple items.

Unlike SSD or Faster R-CNN, this algorithm approaches detection as a regression problem, generating probabilities associated with the identified classes in a single run. Its main advantages are its speed, which allows real-time detection; its high accuracy, characterised by a low error rate; and its high learning capacity, making it an efficient tool for various applications (Pérez-Aguilar et al., 2024). The creation of the dataset could be more complex, using platforms such as Roboflow to assign the labels using the artificial intelligence it offers, improving productivity and focusing on training the model with Yolo.

3.1. Incorporation of new diseases to enhance the efficiency of the model.

Implementing new diseases not present in the model performed in this research provides an essential strategy to cover more disease identifications and expand its capacity to predict new diseases. This will allow the model to gradually increase its detection of diseases affecting bananas and keep the farmer updated with new developments in the crop.

3.2. Impact of the deep learning model

One of the most innovative models is YOLO, a deep learning model that trains with a customised dataset to detect objects in videos and images in real time. The provided libraries allow it to be implemented on any platform, allowing the creation of models to perform specific tasks. Each version of YOLO brings new features, such as improved performance and better detection.

3.3. Banana production in Ecuador and innovations

Projections for the future suggest that banana production in Ecuador will be a dynamic scenario in which technology, sustainability, and marketing will be key (Sánchez et al., 2024). Maintaining optimal banana production is critical through technologies that enable trade sustainability, strategic data-driven decision-making and forecasting, and managing and contributing to the farmer's economic growth.

4. CONCLUSIONS

Technology, day by day, is present in solving problems in different primary, secondary, and tertiary sectors. On the other hand, every year, artificial intelligence has new improvements and innovations for specific tasks, such as improving our lifestyle, automating processes, managing information, and solving problems. Machine learning is fundamental to creating models that allow for solving specific problems. Complex algorithms greatly help create models through a dataset and train them to obtain a powerful tool.

The model trained with the three banana diseases: moko, bacteriosis, and Black Sigatoka. It has allowed the implementation in the agricultural sector in the banana Luz Divina 4, allowing optimal management of its raw material for phytosanitary diseases controlled by technology. The development of the machine learning model and its implementation in the mobile application was fundamental in the innovation in the detection of diseases, a tool of utmost importance for the farmer, allowing them to identify the different affectations in his banana plantation.

References

1. Acosta Espinoza, J. L., León Yacelga, A. R. L., & Sanafria Michilena, W. G. (2022). Las aplicaciones móviles y su impacto en la sociedad. Revista Universidad y Sociedad, 14(2), 237–243. http://scielo.sld.cu/scielo.php?script=sci_abstract&pid=S2218-36202022000200237&lng=es&nrm=iso&tlng=es
2. Adriano-Anaya, M. de L., Matías-Castillo, S., Moreno-Castillo, B., Vázquez-Ovando, A., & Salvador-Figueroa, M. (2023). Mezcla de extracto alcohólico de clavo (Sysygium aromaticum) y ajo (Allium sativum) en el control de la Sigatoka negra en plátano 'Macho'. Revista mexicana de fitopatología, 41(1), 82–92. https://doi.org/10.18781/r.mex.fit.2207-3
3. Aguilar-Anccota, R., Arévalo-Quinde, C. G., Morales-Pizarro, A., & Galecio-Julca, M. (2021). Hongos asociados a la necrosis de haces vasculares en el cultivo de banano orgánico: Síntomas, aislamiento e identificación, y alternativas de manejo integrado. Scientia Agropecuaria, 12(2), 249–256. https://doi.org/10.17268/SCI.AGROPECU.2021.028
4. Aguilar-Anccota, R., Ruiz, W. R., Morales-Pizarro, A., Rafael-Rutte, R., Tirado-Lara, J., Saucedo-Bazalar, M., Tuesta-Albán, C., Apaza-Apaza, S., & Teodor, K. K. (2021). Pudrición blanda en el pseudotallo de banano orgánico (Musa sp): Sintomatología, caracterización cultural y bioquímica, patogenicidad y alternativas de manejo. Scientia Agropecuaria, 12(4), Article 4. https://doi.org/10.17268/sci.agropecu.2021.061
5. Aroca, I. A. A., Vergara-Romero, A., & Almeida, I. B. P. (2023). Las Redes neuronales convolucionales ResNet-50 para la detección de gorgojo en granos de maíz. Scientia Agropecuaria, 14(3), Article 3. https://doi.org/10.17268/sci.agropecu.2023.034
6. Gil-Vera, V. D., & Quintero-López, C. (2021). Predicción del rendimiento académico estudiantil con redes neuronales artificiales. Información tecnológica, 32(6), 221–228. https://doi.org/10.4067/S0718-07642021000600221
7. Martínez-Solórzano, G. E., & Rey-Brina, J. C. (2021). Bananos (Musa AAA): Importancia, producción y comercio en tiempos de Covid-19. Agronomía Mesoamericana, 32(3), 1034–1046. https://doi.org/10.15517/am.v32i3.43610
8. Pérez-Aguilar, D. A., Pérez-Aguilar, J. M., Pérez-Aguilar, A. P., Risco-Ramos, R. H., & Malpica-Rodriguez, M. E. (2024). Inspección de subestaciones eléctricas: YOLOv5 en la identificación de puntos calientes mediante imágenes térmicas. Ingenius, 31, Article 31. https://doi.org/10.17163/ings.n31.2024.04
9. Punguil, D. G. F. (2023). Algoritmos de Deep Learning utilizando Tensorflow para el Tratamiento de Datos de Producción Científica. Tesla Revista Científica, 3(2), Article 2. https://doi.org/10.55204/trc.v3i2.e226
10. Quisaguano, L. R., Camalle, T. G., & Toca, J. W. (2022). Análisis comparativo de entornos de desarrollo móvil. Ciencia Latina Revista Científica Multidisciplinar, 6(4), Article 4. https://doi.org/10.37811/cl_rcm.v6i4.2950
11. Sánchez, V. M. J., Pizarro, N. A. B., & Orellana, M. V. E. (2024). Evolución y proyección de la

producción agrícola (Banano y Café) en Ecuador en el periodo 2012-2025. Revista InveCom / ISSN en línea: 2739-0063, 4(2), Article 2. https://doi.org/10.5281/zenodo.13386325

12. Serrano, L. A. L., Sisalima, M. F. A., Velásquez, N. A. B., & Pineda, Y. L. B. (2020). Ecuador: Análisis comparativo de las exportaciones de banano orgánico y convencional e incidencia en la Balanza Comercial, 2018. Revista Científica y Tecnológica UPSE, 7(2), Article 2. https://doi.org/10.26423/rctu.v7i2.521
13. Torres Solís, C. A., & Quiroz Juárez, M. A. (2023). Convergencia de la inteligencia artificial y la nanotecnología. Mundo nano. Revista interdisciplinaria en nanociencias y nanotecnología, 16(31). https://doi.org/10.22201/ceiich.24485691e.2023.31.69775
14. Vidal-Silva, C. L., Sánchez-Ortiz, A., Serrano, J., & Rubio, J. M. (2021). Academic experience in rapidly developing web information systems with Python and Django. Formación universitaria, 14(5), 85–94. https://doi.org/10.4067/S0718-50062021000500085
15. Vilca Paredes, J. S. (2020). Análisis de riesgo para préstamos bancarios. Revista de Investigación Estudiantil Iluminate, 47. http://revistasbolivianas.umsa.bo/scielo.php?script=sci_abstract&pid=&lng=pt&nrm=iso&tlng=