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Teresina

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RAQUEL MOURA ARAÚJO NOLÊTO

SISTEMA MÓVEL DE IDENTIFICAÇÃO PARA GALINHAS CAIPIRA DA RAÇA CANELA-PRETA

Dissertação apresentada ao Programa de Pós-Graduação em Zootecnia Tropical da Universidade Federal do Piauí como requisito para obtenção do título de Mestre em Zootecnia Tropical.

Orientador: Dr. Natanael Pereira da Silva Santos

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Dedico

Ao meu esposo, filho, irmãs e pais.

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LISTA DE SIGLAS E ABREVIATURAS

ABPA	Associação Brasileira de Proteína Animal
AVIANIDCP	Identificação Aviária de Canela-Preta
CAPES	Coordenação de Aperfeiçoamento de Pessoal de Nível Superior
CCA	Centro de Ciências Agrárias
CNN	*Convolutional Neural Networks*
CEUA	Comissão de Ètica no Uso de Animais
EMBRAPA	Empresa Brasileira de Pesquisa Agropecuária
EMO	Otimização Multiescala Eficiente
GAN	*Generative Adversarial Network*
IA	Inteligência Artificial
LED	*Light Emitting Diode*
LSTM	*Long Short Term Memory – Memória Longa de Curto Prazo*
MAE	Erro Médio Absoluto (*Mean Absolut Error*)
mAP	*mean Average Precision*
MRM	Módulo Residual Multicamadas
MSAnet	Rede Neural Convolucional Multiescala
PIB	Produto Interno Bruto
RCNN	*Region-based CNN*
ResNet	*Residual Network*
RNA	Rede Neural Artificial
RNC	Rede Neural Convolucional
SEDUC	Secretaria de Estado da Educação
SSD	*Solid State Drive* – Unidade de estado sólido
UFPI	Universidade Fderal do Piauí
YOLO	*You Only Look Once* (“olhe apenas uma vez”)
WoS	*Web of Science*

RESUMO

O aumento significativo de criatórios de galinhas caipiras, especialmente da raça Canela-Preta, no estado do Piauí, ressalta a necessidade de superar desafios relacionados ao uso limitado de recursos tecnológicos no controle da produção avícola. Inovações tecnológicas impulsionam este cenário promissor, respondendo à crescente demanda por soluções eficazes de identificação e monitoramento de aves caipiras em diversos ambientes. O objetivo geral desta pesquisa foi desenvolver um aplicativo de identificação de galinhas da raça canela-preta para smartphones, mediante o emprego de inovações tecnológicas e algoritmos avançados. Para o desenvolvimento do aplicativo, utilizou-se 466 imagens de 152 galinhas da raça canela-preta. Essas imagens foram usadas para treinar e ajustar um algoritmo de identificação, permitindo aprender e reconhecer características específicas dessa raça. A arquitetura desse algoritmo foi desenvolvida com base em experimentações e avaliações de desempenho. Utilizou-se o *framework* YOLOv8 para detecção de objetos e localização das galinhas nas imagens. O algoritmo *Random Forest* foi aplicado para análise de características específicas e classificação precisa do animal. No desenvolvimento do aplicativo, optou-se por uma abordagem em que os usuários realizaram a captura e transmissão de imagens em tempo real para um servidor central, recebendo, em contrapartida, resultados de identificação do animal. A análise estatística dos resultados de reconhecimento revelou uma taxa média de precisão de 99,4% e uma taxa de erro médio de 0,04%, evidenciando, assim, a confiabilidade da abordagem. O aplicativo desenvolvido revelou-se uma ferramenta promissora para a identificação precisa e eficiente desses animais.

Palavras-chave: aves domésticas; inteligência artificial; reconhecimento de animais; processamento de imagens; visão computacional.

ABSTRACT

The significant increase in free-range chicken farms, especially of the Canela-Preta breed, in the state of Piauí, highlights the need to overcome challenges related to the limited use of technological resources in controlling poultry production. Technological innovations drive this promising scenario, responding to the growing demand for effective solutions for identifying and monitoring free-range birds in different environments. The general objective of this research was to develop an application for identifying black cinnamon chickens for smartphones, using technological innovations and advanced algorithms. To develop the application, 466 images of 152 black cinnamon chickens were used. These images were used to train and adjust an identification algorithm, allowing it to learn and recognize specific characteristics of this breed. The architecture of this algorithm was developed based on experiments and performance evaluations. The YOLOv8 framework was used to detect objects and locate the chickens in the images. The Random Forest algorithm was applied to analyze specific characteristics and accurately classify the animal. When developing the application, an approach was chosen in which users captured and transmitted images in real time to a central server, receiving, in return, animal identification results. Statistical analysis of the recognition results revealed an average accuracy rate of 99.4% and an average error rate of 0.04%, thus demonstrating the reliability of the approach. The developed application proved to be a promising tool for the accurate and efficient identification of these animals.

Keywords: domestic birds; artificial intelligence; animal recognition; image processing; computer vision.

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1 INTRODUÇÃO

No contexto da avicultura, especialmente na região Nordeste do Brasil, a criação de galinhas caipiras destaca-se como uma prática intimamente ligada à agricultura familiar. Esta modalidade de agricultura é caracterizada pela realização em propriedades de pequeno porte, onde a mão de obra é predominantemente familiar (De Zen *et al*., 2019). A produção de alimentos neste formato, tem como foco principal o consumo interno da própria família, enquanto o excedente é comercializado localmente. Atualmente, a agricultura familiar é reconhecida como uma oportunidade vital para impulsionar o desenvolvimento da produção rural, pois contribui significativamente para a redução da pobreza e desempenha um papel crucial na prevenção do êxodo rural (Moura; Silva, 2012).

Segundo Martins Júnior (2018), a criação de galinhas caipira é destacada como uma prática economicamente viável, valorizada pelo crescente reconhecimento de alimentos produzidos de maneira sustentável, sem causar danos significativos ao meio ambiente e sem submeter as aves a sofrimentos, além do uso reduzido de produtos químicos.

Essa atividade desempenha um papel significativo na economia da produção familiar (Martins Júnior, 2018). No entanto, é imprescindível realizar ajustes na gestão dos plantéis, alinhando-a à realidade das famílias, a fim de viabilizar a integração de tecnologias que possam otimizar significativamente o rendimento da produção

O crescente número de criatórios de galinhas caipira, notadamente da raça Canela-Preta, no estado do Piauí, destaca a urgência de superar desafios associados ao uso limitado de recursos tecnológicos para o controle da produção. Uma solução viável para essa demanda é o desenvolvimento de um aplicativo móvel para smartphones que possibilite o registro individual das aves em tempo real.

A indústria pecuária está adotando essa abordagem inovadora para assegurar a identificação precisa e eficaz dos animais, utilizando dispositivos móveis, como smartphones e tablets (Costa; Klein e Vieira, 2014). Essa abordagem se baseia em sistemas de reconhecimento de imagens, tornando mais simples o processo de identificação dos animais. A ideia é associar cada animal a um registro digital, permitindo o acesso a informações em tempo real, formando um banco de dados que são a base para os sistemas que auxiliam nas tomadas de decisão, indicadores de desempenho dos processos produtivos (Fontoura *et al*., 2018).

Logo, o objetivo geral desta pesquisa foi desenvolver um aplicativo para smartphones destinado à identificação de galinhas da raça canela-preta, mediante o emprego

de inovações tecnológicas e algoritmos avançados. O intuito é de superar desafios no controle da produção avícola em criatórios de galinhas caipiras no estado do Piauí, especialmente da raça canela-preta. O foco é futuramente automatizar a fenotipagem dessas aves, visando aprimorar a eficiência e garantir o bem-estar animal.

Esta Dissertação está estruturada conforme normas estabelecidas pelo Manual de Normalização de Monografia, Dissertação e Tese da Universidade Federal do Piauí. O Capítulo I segue as normas de publicação da revista *Journal Ciência Rural* (ISSN Eletrônico: 1678-4596). e II segue as normas de publicação da revista *Journal of Food Engineering* (ISSN 0260-8774). No Capítulo I, é conduzida uma análise bibliométrica e revisão sistemática dos trabalhos correlatos, evidenciando os principais temas abordados. Por sua vez, o Capítulo II detalha a solução proposta neste estudo, oferecendo uma minuciosa explanação sobre a concepção e construção do sistema destinado ao reconhecimento de aves, englobando também a avaliação do algoritmo desenvolvido. Essa avaliação contempla a análise dos objetivos alcançados e os desafios a serem enfrentados para futuras melhorias. A organização do estudo foi cuidadosamente elaborada para acomodar os diversos tópicos abordados. Inicialmente, uma revisão de literatura foi apresentada como base teórica, incorporando as referências bibliográficas utilizadas nos Capítulos I e II.

2 REFERENCIAL TEÓRICO

2.1 Raça Canela-Preta

As galinhas domésticas (*Gallus gallus domesticus*) foram trazidas para o Brasil pelos colonizadores portugueses por volta do ano de 1500. Ao longo dos séculos, essas aves se reproduziram naturalmente através de cruzamentos aleatórios e, sob a influência das condições ambientais, deram origem a diversas raças brasileiras, que agora são encontradas em todas as regiões do país (Carvalho, 2016).

As primeiras galinhas da raça Canela-Preta foram identificadas em 2008 pelo Dr. Marcos Jacob de O. Almeida no município de Curral Novo do Piauí e em municípios vizinhos, durante ações da Secretaria de Estado da Educação - SEDUC e Embrapa Meio-Norte (Sarmento *et al*., 2017). Encontradas no estado do Piauí e possivelmente em outros estados do Nordeste brasileiro, as galinhas da raça Canela-Preta são criadas a campo por pequenos agricultores (Carvalho *et al*., 2017).

Em algumas regiões, aves da raça Canela-Preta são também conhecidas como “galinhas Jacu”, e estão presentes em pequenas comunidades rurais, quilombolas e indígenas em todo estado do Piauí, e possivelmente em outros estados do Nordeste. Vinte e oito municípios do Piauí e oito municípios no Maranhão contam com a presença de criadores de referência dessa raça (Sarmento *et al*., 2017).

Animais dessa raça caracterizam-se por possuir carne de coloração escura, muito apreciado pela população local. Estas, mostram-se adaptadas, visto que são criadas em condições de clima tropical, e de forma predominantemente extensiva com pouco ou nenhum investimento tecnológico e controle zootécnico (Carvalho *et al*., 2017). Aves adaptadas ao clima tropical, resistentes a doenças e parasitas, sendo consideradas de elevada rusticidade (Fonteque *et al*., 2014).

As aves possuem dupla aptidão produtiva, tanto para serem escolhidas visando a produção de ovos quanto para a produção de carne. As fêmeas iniciam a fase de produção de ovos a partir dos seis meses de idade. Nessa raça, é possível observar ovos com coloração variada, incluindo tons de marrom, vermelho, azul e verde. As aves alcançam um peso médio adequado para comercialização aos seis meses de idade em um sistema semi-intensivo, e acima de oito meses em um sistema extensivo (Carvalho *et al*., 2016).

2.2 Visão Computacional na Avicultura

Visão computacional é o campo da ciência que lida com a habilidade das máquinas de "verem" e compreenderem o mundo ao seu redor através da análise de imagens capturadas por dispositivos como câmeras de vídeo, sensores e scanners. Esses dados possibilitam que as máquinas identifiquem, manipulem e compreendam os objetos contidos em uma imagem (Milano; Honorato, 2014).

Santos *et al*. (2020), proporcionou uma definição clara e abrangente para o conceito de visão computacional: trata-se de uma área da inteligência artificial focada na extração de informações a partir de imagens digitais. Nesse contexto, a técnica de detecção de objetos entra em cena, abrangendo a localização e identificação de objetos específicos em uma imagem.

Com o avanço da tecnologia de visão computacional, vários estudos têm se concentrado no diagnóstico computadorizado de doenças em aves. Zhuang *et al.* (2018) e Zhuang e Zhang (2019) demonstraram a detecção precoce de aves doentes usando técnicas de processamento de imagens e aprendizado profundo. Wang *et al.* (2017) e Wang *et al.* (2019) investigaram métodos de monitoramento e identificação de aves doentes com base em comportamento, informações fisiológicas e fezes. Liu *et al.* (2020) propuseram a detecção de aves doentes por meio de anomalias sonoras.

Aydin (2017) também contribuiu com pesquisas de visão computacional, focando na identificação de problemas de claudicação em aves. Okinda *et al.* (2019) exploraram um sistema de visão de máquina para detecção precoce e previsão de doenças aviárias. Esses estudos evidenciam os avanços significativos na aplicação da visão computacional para o diagnóstico e monitoramento de saúde em aves, oferecendo uma abordagem abrangente para melhorar a detecção e o tratamento de doenças nesse contexto.

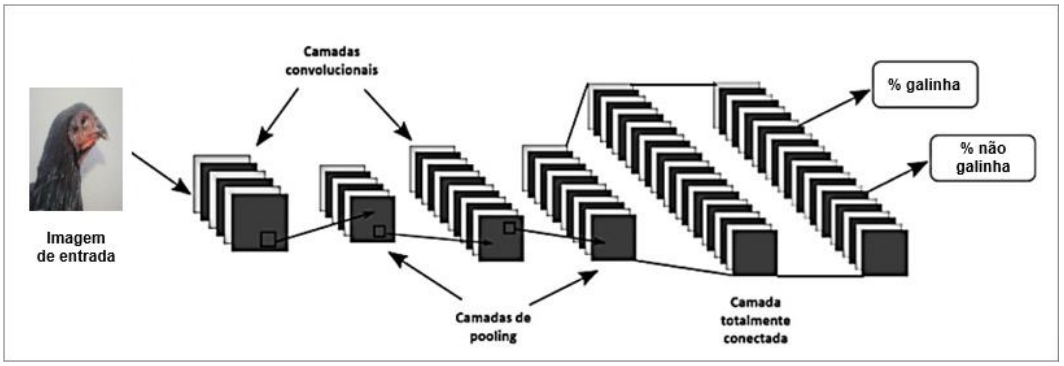
2.3 Redes Neurais Convolucionais (RNC)

As Redes Neurais Convolucionais (RNCs), constituem um tipo particular de Rede Neural Artificial (RNA). Estas redes foram propostas pelo pesquisador francês Yann LeCun e sua equipe em 1998 (Lecun *et al*., 1998). As RNCs desempenham um papel fundamental na área da visão computacional, onde são projetadas para analisar imagens e extrair informações significativas, possibilitando a realização de tarefas como classificação e

detecção de objetos (Krizhevsky; Sutskever; Hinton, 2012).

Uma das limitações reconhecidas das Redes Neurais Convolucionais (RNCs) é a demanda por uma grande quantidade de dados rotulados para identificar padrões ou características significativas. Geralmente, uma RNC é composta por três elementos essenciais: a camada de convolução, a camada de pooling e a camada totalmente conectada, conforme discutido por Rodrigues (2018). Esses elementos servem como blocos fundamentais nas RNCs, permitindo à rede aprender representações hierárquicas de características em imagens e executar tarefas complexas de visão computacional. Esses blocos são padrões comuns em diversas arquiteturas básicas de RNC, como exemplificado na Figura 1.

Figura 1 - Representação visual da arquitetura RNC, identificando a galinha Canela-Preta.



2.3.1 Camadas Convolucionais

A camada convolucional em uma *Rede Neural Convolucional* (RNC) tem a responsabilidade de extrair características da entrada usando filtros convolucionais, também conhecidos como *kernels* convolucionais. Estes filtros são projetados para aprender automaticamente padrões significativos durante o treinamento da rede neural, adaptando-se aos dados de entrada para identificar características importantes para a tarefa em questão, como bordas, texturas, ou outros padrões relevantes para a classificação ou detecção de objetos, por exemplo (Khan *et al*., 2018).

Dentro de uma camada convolucional, as unidades são como pequenos elementos de processamento que trabalham juntos para entender uma imagem ou conjunto de dados. Essas unidades são organizadas em mapas de características, que são como diferentes áreas da imagem em que a rede está focando sua atenção. Cada uma dessas unidades está "ligada" a uma parte da imagem anterior, e isso é feito através do que se chama de "filtros". (Lecun

et al., 2015).

Esses filtros percorrem os dados da imagem e destacam características específicas, como bordas, cores, texturas, entre outros detalhes relevantes. Durante o treinamento, à medida que a imagem é processada, os filtros são ajustados para se ativarem quando identificam padrões comuns em várias amostras, como bordas ou cores distintas (Rodrigues, 2018).

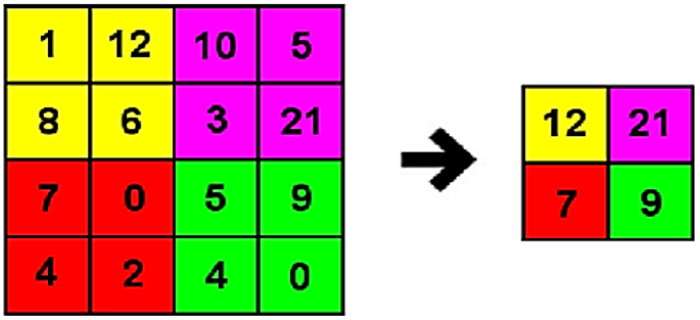
À medida que a entrada passa pela rede, os filtros aprendem a reconhecer estruturas mais complexas e detalhadas. A utilização de um maior número de filtros convolucionais pode permitir a extração de um espectro mais amplo de características, porém isso também demanda mais recursos computacionais e memória. Portanto, ao projetar a arquitetura da rede, é necessário encontrar um equilíbrio entre a quantidade de filtros utilizados e os recursos disponíveis (Rodrigues, 2018).

2.3.2 Camadas de Pooling

Conforme (Karpathy *et al*., 2017), a camada de pooling tem a principal função de diminuir as dimensões dos dados de entrada. Tipicamente, após uma camada convolucional, aplica-se uma camada de pooling. Isso permite que as camadas de convolução subsequentes recebam uma representação diferente dos dados, o que ajuda a rede a aprender várias representações dos dados. Esse processo auxilia na prevenção do overfitting, que é quando o modelo captura não apenas os padrões reais nos dados, mas também o ruído ou a variabilidade aleatória presente nos dados de treinamento.

Uma técnica amplamente empregada para realizar o pooling é conhecida como maxpooling. Nesse método, reduz-se partes menores dos dados originais, selecionando o valor máximo em cada uma dessas sub-regiões (Figura 2). Isso resulta na redução do tamanho da imagem por um fator de m x n, onde m e n são as dimensões do filtro usado para o maxpooling (Rodrigues, 2018).

Figura 2 - Exemplo de max-pooling com um filtro 2x2 em uma imagem que é originalmente 4x4 (Ferreira, 2017).

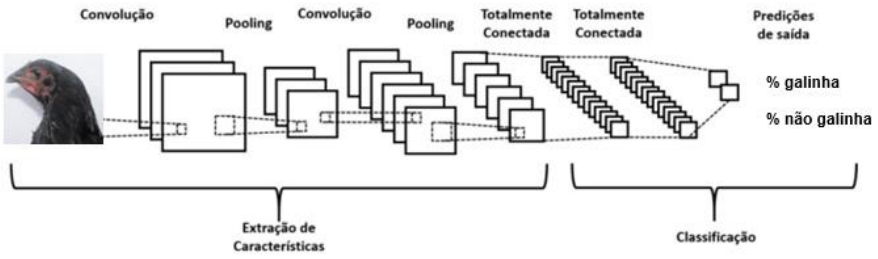


A técnica de pooling é vantajosa para a rede neural, pois reduz a quantidade de dados que são passados para a camada seguinte. Além disso, ela ajuda a melhorar a regularização da rede, o que, por sua vez, reduz os custos de memória e capacidade de processamento (Vargas; Paes; Vasconcelos, 2016).

2.3.3 Camadas Totalmente Conectadas

Após as camadas convolucionais e de pooling, as camadas totalmente conectadas são usadas para combinar informações de todas as partes da imagem e gerar a saída desejada, como a classe de um objeto em uma imagem (Rodrigues, 2018). A Figura 3, exemplifica a arquitetura com as três camadas básicas.

Figura 3 - Exemplo de arquitetura RNC, utilizando as camadas básicas de convolução, pooling e totalmente conectadas.



Em resumo, as arquiteturas de RNCs são construídas com camadas convolucionais para extrair características, camadas de pooling para diminuir a complexidade dimensional e camadas totalmente conectadas para a etapa final de classificação.

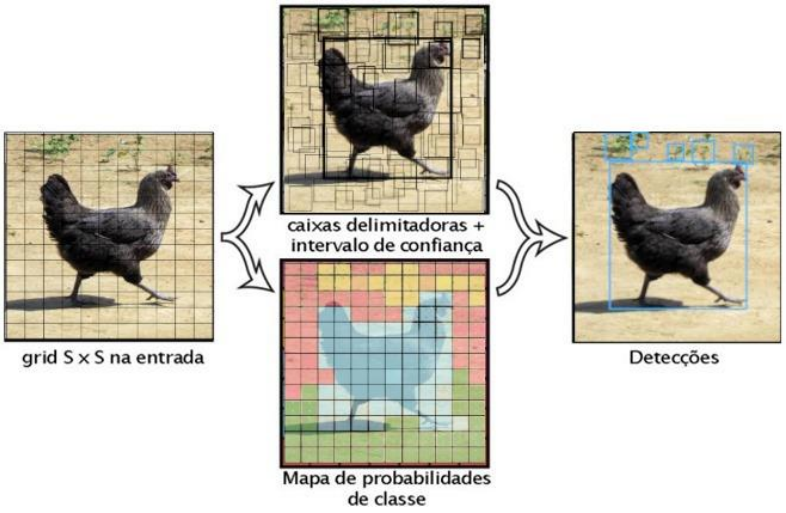
2.4 Detecção e segmentação de imagens

O modelo YOLO (*You Only Look Once*), amplamente reconhecido na detecção de objetos e segmentação de imagens, foi desenvolvido por (Redmon *et al*., 2016). Ele ganhou popularidade devido à sua notável combinação de alta velocidade e precisão.

A série de algoritmos YOLO é conhecida por ser uma das opções mais eficientes e rápidas disponíveis até o momento. Em particular, o algoritmo YOLOv8, lançado em 2023, tem apresentado a mais alta precisão registrada, conforme observado por (Lou *et al*., 2023).

Conforme ilustrado na Figura 4, o conceito central do mecanismo usado no modelo Yolo é dividir a imagem em regiões delimitadas chamadas de *bounding box*. O centro de cada *bounding box* é posicionado sobre o objeto detectado que precisa ser classificado (Redmon *et al*., 2016).

Figura 4 - Apresentação da operação da rede YOLO usando caixas delimitadoras (*bounding box*).



O algoritmo divide a imagem de entrada em uma grade de tamanho S × S. Se um objeto estiver localizado dentro de uma célula da grade, essa célula será responsável por detectar esse objeto. Cada célula da grade faz previsões para B caixas delimitadoras, scores de confiança associadas a essas caixas e a probabilidade de pertencer a uma das C classes possíveis. Essas previsões são representadas como um tensor de dimensões S x S x (B x 5 + C) (Du, 2018).

Cada caixa delimitadora é composta por 5 previsões: x, y, w, h e um intervalo de confiança. Aqui, x e y representam as coordenadas do centro da caixa, enquanto w e h

representam o comprimento e a altura previstos da caixa. O intervalo de confiança reflete a estimativa do modelo sobre a sobreposição (IOU) entre as caixas. Além disso, em cada célula da grade que contém uma caixa delimitadora, o modelo faz uma estimativa da probabilidade de pertencer a uma das C classes possíveis, denotada como P ($Class_i$/Object) para o objeto detectado. Importante notar que, independentemente do número de objetos detectados, apenas um conjunto de probabilidades é estimado para cada célula da grade (Carboni, 2021). Durante o teste, todas as estimativas condicionais são multiplicadas, e assim obtem-se a estimativa da classe do objeto conforme especificado na Equação (1).

$$P(Class_i/Object) * P(Object) * IOU^{realprevista} = P(Class_i) * IOU^{realprevista} \quad (1)$$

2.5 *Machine Learning*

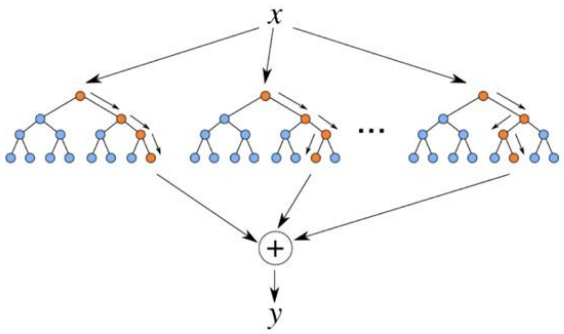
O algoritmo *Random Forest* é uma técnica de aprendizado de máquina que trabalha construindo diversas árvores de decisão durante o treinamento e combinando as previsões de cada árvore para obter uma predição final. Essa abordagem em conjunto ajuda a evitar o ajuste excessivo e melhora a precisão das previsões em comparação com o uso de uma única árvore de decisão (Breiman, 2001).

A principal ideia por trás do algoritmo *Random Forest* é criar um conjunto de árvores de decisão ("floresta"), onde cada árvore é construída de forma independente utilizando conjuntos de dados de treinamento diferentes, obtidos por amostragem aleatória com reposição (técnica chamada "bagging"). Durante a divisão de cada nó na árvore, o algoritmo considera apenas um subconjunto aleatório das características, o que aumenta a diversidade entre as árvores individuais (Liaw; Wiener *et al*., 2002).

Devido à sua capacidade de lidar com conjuntos de dados extensos e complexos, e sua eficácia em resolver desafios de classificação e regressão, o algoritmo Random Forest é amplamente empregado em diversas áreas, como ciências ambientais, saúde, finanças e outros campos (Cutler *et al*., 2007).

O algoritmo *Random Forest* é uma coleção de várias árvores de decisão independentes (Figura 5). Cada árvore é construída com base em uma amostra aleatória do conjunto de dados de treinamento. Essa amostragem aleatória é conhecida como "*bootstrapping*". Cada árvore é uma "floresta" em si mesma. No Treinamento Individual das Árvores, cada árvore é treinada para fazer previsões com base nas características das instâncias de treinamento (Teloken *et al*., 2016).

Figura 5 - Funcionamento do método de classificação *Random Forest* (Teloken *et al*., 2016).



Onde, x é a entrada da imagem e y é a saída da imagem.

Durante o treinamento de cada árvore, uma seleção aleatória de características é considerada em cada divisão do nó, tornando as árvores ainda mais diferentes entre si. Após o treinamento das árvores, quando é necessário fazer uma previsão para uma nova instância (por exemplo, uma imagem de uma ave desconhecida), cada árvore na floresta faz sua própria previsão. A classe que obtém a maioria das previsões entre as árvores é a previsão final da *Random Forest*. Essa abordagem é conhecida como "votação" (Teloken *et al*., 2016).

2.6 Métricas de Avaliação

Métricas de avaliação são medidas quantitativas utilizadas para avaliar o desempenho de modelos em diversas áreas, como aprendizado de máquina, visão computacional e processamento de linguagem natural. Elas ajudam a quantificar o quão bem um modelo se ajusta aos dados de treinamento e quão eficaz é na realização de previsões ou classificações em dados não vistos (De Oliveira *et al*., 2019). Avalia os algoritmos no contexto das fases de treinamento e predição empregados.

As métricas de avaliação tem como propósito a análise do desempenho de algoritmos, destacando-se duas métricas fundamentais: a acurácia, que mensura a precisão do modelo, e o erro médio absoluto (MAE), uma medida que quantifica a discrepância média entre as previsões do modelo e os valores reais.

2.6.1 Acurácia (A)

Conforme Freitas *et al*. (2019), a acurácia em problemas de classificação representa o número de previsões corretas feitas pelo modelo em relação ao total de previsões feitas. Essa métrica avalia a precisão completa de um classificador, indicando a porcentagem total de instâncias previstas corretamente ao serem confrontadas com dados não observados, com base em um modelo treinado (Hossin; Sulaiman, 2015). A acurácia é medida através do número de verdadeiros positivos mais o número de verdadeiros negativos dividido pelo total de elementos da matriz, conforme descrito por Carvalho *et al*. (2011). A fórmula é expressa da seguinte maneira:

$$Acurácia\ (A) = \frac{VP + VN}{VP + VN + FP + FN}$$

Sendo: verdadeiros positivos (VP), amostras corretamente classificadas como positivas, verdadeiros negativos (VN), amostras corretamente classificadas como negativas; falsos positivos (FP), amostras incorretamente classificadas como positivas; e os falsos negativos (FN) amostras incorretamente classificas como negativos.

2.6.2 Erro Médio Absoluto (*Mean Absolute Error* - MAE)

Durante o treinamento, a função de perda é uma importante métrica de avaliação, e é função que se deseja minimizar neste processo. Esta deve ser avaliada tanto sobre o conjunto de treinamento quanto sobre o conjunto de validação. Proposto por Sarmento (2006), o erro médio absoluto dos resíduos (MAE), é calculado através do somatório dos desvios entre a informação observada com a estimada, dividido pelo número de observações, como indicado a seguir:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

em que, N é a quantidade de imagens utilizadas para observar, yi é o valor esperado e ŷi é o valor de predição. Quanto menor o erro médio absoluto dos resíduos, melhor o modelo ajustado.

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CAPÍTULO I

Poultry recognition and detection: literature systematization with an emphasis on innovations using neural networks and machine learning

Poultry recognition and detection: literature systematization with an emphasis on innovations using neural networks and machine learning

Reconhecimento e detecção de aves: sistematização da literatura com ênfase em inovações utilizando redes neurais e aprendizado de máquina

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ABSTRACT

Advances in the development of new approaches for bird recognition in agriculture represent a significant challenge, characterized by the inherent complexity of their implementation. This article's main objective is to critically and comprehensively analyze the trends, methods and main contributions of image processing used to monitor and identify birds in the context of agriculture, through a bibliometric study and a systematic review. Data were collected from a bibliometric study to map academic production, using the Web of Science (WoS) platform and the Bibliometrix package of the R software. From the search on the Web of Science platform, over the last 5 years, 150 articles on bird recognition and detection using neural networks and machine learning, with collaboration from 890 researchers in 30 countries. The top 10 countries that published the most on the topic total 121 publications, with emphasis on China, followed by the United States, Indonesia and Korea. 97 journals were identified as dissemination channels, and the most relevant keywords included "deep learning", "salmonella", "biosensor" and "chicken". With this research it was possible to observe the use of neural networks in

poultry farming and their effectiveness in predicting the production and characteristics of individual birds.

Key-words: bird identification; computer vision; convolutional neural network.

RESUMO

O avanço no desenvolvimento de novas abordagens para o reconhecimento de aves na agropecuária representa um desafio significativo, caracterizado pela complexidade inerente à sua implementação. Este artigo tem como objetivo principal analisar criticamente e de forma abrangente as tendências, métodos e principais contribuições do processamento de imagem utilizadas para monitorar e identificar aves no contexto da agropecuária, por meio de um estudo bibliométrico e uma revisão sistemática. Os dados foram coletados a partir de um estudo bibliométrico para mapear a produção acadêmica, utilizando a plataforma Web of Science (WoS) e o pacote Bibliometrix do software R. A partir da busca na plataforma Web of Science foram identificados, nos últimos 5 anos, 150 artigos sobre reconhecimento e detecção de aves utilizando redes neurais e aprendizado de máquina, com colaboração de 890 pesquisadores em 30 países. Os 10 principais países que mais publicaram sobre o tema somam 121 publicações, com destaque para a China, seguida pelos Estados Unidos, Indonésia e Coréia. Foram identificados 97 periódicos como canais de disseminação, e as palavras-chave mais relevantes incluíram "deep learning", "salmonella", "biosensor" e "chicken". Com essa pesquisa foi possível observar o uso de redes neurais na avicultura e sua eficácia na previsão da produção e características de aves individuais.

Palavras-chave: identificação de aves; visão computacional; rede neural convolucional.

INTRODUCTION

With the growing interest of agricultural researchers in precision agriculture and smart agriculture, it is seen a significant increase in the application of computer vision technology in the agricultural production management system (BENJAMIN; YIK, 2019; ASTILL et al.

2020; ZHENG et al. 2021). The automatic application of computer vision technology has provided a remarkable improvement in agricultural production management (LIU et al. 2020; LI et al. 2020).

In Brazil, according to the report by the Associação Brasileira de Proteína Animal (Brazilian Animal Protein Association) – ABPA (2024), poultry farming plays an important role, representing 1.5% of the national Gross Domestic Product (GDP) and generating almost 4 million direct and indirect jobs in both production and industry. Over the last few decades, chicken meat, the main product of Brazilian poultry farming, has consolidated its presence in several international markets, adopting strict standards and put the country as the second largest global producer and the main exporter. In 2023, chicken exports resulted in almost US$4.822 million tons to 145 countries.

Over time, poultry farming became strong thanks to technological advances, genetic improvement, effective health control and financing available to the sector. These factors helped so that Brazil achieved this international recognition due to product quality and sanitary excellence (PINHEIRO, 2014; ROSSETTI, 2014). The fast technology evolution has led to innovative approaches, especially aimed at overcoming challenges related to identifying and monitoring animals in agricultural environments (BENJAMIN; YIK, 2019).

In this work, the goal was to critically and comprehensively analyze the trends, methods and main contributions of image processing used to monitor and identify birds in the context of agriculture, through a bibliometric study and a systematic review.

For the present study, we opted for a bibliometric research method, which allows indicators to be used to establish prognoses and trends in scientific production in different fields of research, making it possible to carry out analyzes of relevant articles in research areas and themes.

In summary, the research was conducted following the essential steps for bibliometric

research, as proposed by ZUPIC & CATER (2015): study design; data collection; data analysis; visualization and organization of data.

Study Design

The database selected for this study was extracted from the main Web of Science (WoS) collection, which has broad coverage and scope of indexed scientific articles, offering a wide variety of reliable information sources. For the bibliometric analysis, an extensive resource for scientific mapping was used the Bibliometrix package from the R software (ARIA; CUCCURULLO, 2017).

Data Collection

It focused on the perspective of scientific production concentrated on publications on bird recognition and detection based on neural networks and machine learning. Compared to other platforms, this WoS resource allowed grouping of academic articles by interest, as well as searching by keywords, authors, and work titles.

The search for data for bibliometric analysis was carried out through the virtual library Portal de Periódicos, from the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Coordination for Personal Improvement of Higher Education - (Capes) and, subsequently, access was made to the Main Collection of the International Database Web of Science (WoS), the date range chosen to carry out the research was from January 2019 to February 2024. Some boolean terms and operators were considered, used to refine and specify the search results: ((ALL=(convolutional neural networks) AND ALL=(machine learning)) AND (ALL=(free range poultry farming) OR ALL=(chickens)) AND (ALL=(recognition) AND ALL=(detection))). Where the acronym “ALL” indicates that the search can be carried out in all fields, in the title, summary, keywords. The term “AND” is applicable when it is necessary

for the search results to include all terms, that is, all chosen keywords are searched together. And the “OR” operator is used to combine articles that have any of the selected terms, both alone and together.

In order to offer a more up-to-date set of knowledge, techniques, methodologies, discoveries and technologies available in a specific area, suitable for the use of the tools available to carry out bibliometric analysis, some inclusion criteria were previously established, such as the selected works must contain the terms “convolutional neural networks” and “machine learning”. Furthermore, it is essential to have the words “free range poultry farming” or “chickens”, combined with “recognition” and “detection”.

In the review, the address provided by the first author's research institution was prioritized, including the geographic field of the countries inserted in the approach.

Data Analysis

After the results regarding the publications collected in WoS, all records found were selected and exported to a file in the “BibTex” format (ADRIAANSE; RENSLEIGH, 2013). With the help of R software version 4.2.2, it was possible to perform the bibliometric analysis, using the bibliometrix package. The data obtained were examined in terms of number of publications per year, main countries involved in scientific production on the subject, journals that published the most selected works, in addition to recording the frequency of keywords referring to the main themes involving bird recognition through neural networks and machine learning.

Visualization and organization of data

After importing the data into the Bibliometrix library, the tables and graphs generated by Bibliometrix R (Biblioshiny), and adapted in Excel, were used to organize and present the

results, the last step of the bibliometric method. Due to the large number of documents found, it was decided to present the ranking of the greatest predominant 10 terms within the results.

Research results

From the search on the Web of Science platform, 150 articles were identified covering the topic “bird recognition and detection based on neural networks” and “machine learning” in the last 5 years, with the participation of Chinese, American, Brazilian, Canadians, among others, and affiliates in several institutions distributed in 30 countries, co-authored by 890 researchers and published in 97 journals.

In the study, the distribution of publications in the WoS database by year of publication was examined. The results are shown in **Graph 1**.

In 2019, selected as the starting point for searching for articles, 29 publications were found. This same number of records was maintained in 2020. However, a peculiar observation emerged in 2021, with a slight decrease in the number of publications on the topic under study. A plausible reason for this decrease can be attributed to the pandemic, which possibly impacted the ability of researchers and institutions to conduct research and disseminate their results, a number that grew exponentially again in 2022, with its peak of 35 publications.

Furthermore, this high number compared to previous years can be justified by the growing search for Artificial Intelligence (AI) algorithms, given the great impact on the poultry production area. AI algorithms are capable of processing large amounts of data and identifying complex patterns, which has led to significant improvements in efficiency, productivity and animal welfare (FUENTES et al., 2022).

Regarding the distribution of publications by country among the selected articles, 30 countries were observed, among which stood out the ones that most predominated in their production. The ten countries that published the most on the topic have 121 publications.

Among them, China (101) has the highest number of publications, followed by the United States (4), Indonesia (3) and Korea (3). **Figure 1** shows the full list of these top ten countries.

China stands out as one of the global leaders in neural networks and machine learning, due to its substantial investments in research and development of artificial intelligence technologies (LARSEN, 2022). It has world-renowned universities, advanced research centers and innovative companies that are at the forefront of these areas. It is a country with broad access to high-performance computing resources and advanced infrastructure (LEE, 2019). This allows them to process large volumes of data and train complex neural network models, essential for animal recognition and detection.

It is important to inform that several countries around the world are active in this sector. Brazil, for example, ended the year 2023 with records in chicken meat exports, reaching 5.138 million tons, representing an increase of 6.6% compared to 2022. These numbers, released by ABPA (2024), indicate a positive trend for the year 2024.

Regarding the dissemination of knowledge, 97 journals were identified, channels for propagating the terms researched. **Figure 2** shows the ranking of the 10 journals that published the most on the topic and the number of works published.

Among the 10 most cited journals, "Food Chemistry" and "Sensors and Actuators B-Chemical" stand out with 6 articles each, published with the topic under study between January 2019 and February 2024. "Food Chemistry" is a international peer-reviewed scientific journal dedicated to publishing original research and reviews in the field of food chemistry. The journal covers a variety of topics related to chemistry, biochemistry, and food technology, providing a platform for the dissemination of significant discoveries and scientific advances in the field. And the magazine “Sensors and Actuators B-Chemical”, specializes in science and technologies related to chemical sensors and actuators, which are devices that respond to chemical stimuli. Its scope covers a wide variety of topics within that specific domain. Topics

explored include advances in sensory materials, development of sensing devices, analytical methods, chemical sensors actuation devices and practical application.

A total of 592 keywords were identified in the selected articles. Among them, the most relevant included "deep learning" (with 13 occurrences), "salmonella" (with 6 occurrences), "biosensor" (with 5 occurrences), "chicken" (with 5 occurrences), as may be seen in **Figure 3.**

These keywords are linked to the context of recognizing and detecting birds by making use of neural networks and machine learning techniques. This theme suggests a focus on methods and technologies that uses artificial intelligence and machine learning algorithms to recognize and detect birds in different contexts, ranging from the identification of behavior patterns to the practical application of these methods in poultry farming.

Systematic Review

To group information on bird recognition through images in the area of animal production in the last five years, a filter was carried out on the 150 articles selected in the WoS database. In the synthesis of the systematic review, articles were included if they presented in detail the tools used to identify birds from images, avoiding only mentions in the text. The selection was made based on reading the abstract and conclusion of the 150 articles. Of these, 137 were excluded due to the research approach aimed at recognizing other aspects such as bird excrement or egg fertility, which are not directly related to the visual recognition of the birds themselves.

After screening the articles, 13 studies genuinely related to bird recognition through images were identified, which proved to be highly relevant to this study. These works were selected after a thorough reading, ensuring that the authors effectively detailed the tools used to identify birds.

Table 1 presents a compilation of articles selected from the Web of Science database, highlighting different methods used in the field of bird recognition. These methods cover a variety of techniques, from the use of convolutional neural networks (CNNs) to image processing and machine learning algorithms. Analysis of these articles provided a comprehensive overview of the latest and most effective approaches in the field, promoting a deeper understanding of trends and innovations.

ZHANG & CHEN (2020) approached the development of an automatic detection system for sick chickens. This paper proposed an automatic detection system for sick chickens based on the ResNet residual network. Using broiler birds as an example, the system aimed to improve the accuracy and speed in identifying sick chickens in poultry farming. Through the use enhanced data and training techniques with tens of thousands of iteractions. Compared to traditional systems, this system proved to be more effective, resulting in labor cost savings and improved identification accuracy. The model was trained using a deep neural network and evaluated for accuracy, achieving a recognition rate of up to 95% in identifying sick chickens. The system can be expanded to real-time monitoring and disease diagnosis in other farm animals, with future research focused on improving accuracy for diferente chicken breeds and ages.

Another important work published in 2020 was developed by YE et al., (2020). This study focused in presenting an improved algorithm to detect broiler chicken in a stunned state after an electrical procedure, named YOLO associated to the introduction of a multilayer residual module (MRM). The lgorithm showeda remarkable precision of 96,77%, overcoming other modules by using efficient developing data methods to avoid overfitting, that is when a module captures not only real data pattern, but also the noise or random variation present in training data. YOLO + MRM achieved a detection rate of 180,000 chickens per hour. Positive results include the algorithm's high accuracy, its automatic ability to identify the stunned state

of broilers, and superior performance compared to other models. However, the study does not provide details about the specific number of birds used in the experiment, which could improve the statistical validity of the results. A possible development would be to include this information. Furthermore, it would be interesting to investigate the capacity of the algorithm in different lighting conditions and environments, aiming to evaluate its robustness in real-world scenarios.

The article conducted by WANG et al. (2020) highlighted the successful application of the YOLOv3 model in detecting behaviors in chickens in a self-breeding system. The algorithm, based on YOLOv3, achieved high accuracy in identifying mating and abnormal behaviors, providing technical support to improve the welfare of birds destined for egg production. Automation in detecting behaviors, especially mating frequency, has facilitated the assessment of well-being, enabling informed decisions to create a healthy environment. This promising approach has the potential to improve poultry practices, meeting growing demands for animal welfare and consolidating market trust in companies that demonstrate a commitment to technological innovation and animal welfare. YOLOv3 showed remarkable accuracy rates, ranging from 86.88% to 94.72%, with mating frequency highlighted as a reflective indicator of welfare in self-breeding cages.

However, to upgrade this experiment it is necessary to specify the exact number of animals used, give further detail the methodology for evaluating welfare indicators and explore possible limitations of the YOLOv3 model to detect specific behaviors. These improvements can provide a more solid basis for interpreting results and practical application of findings in the poultry industry.

YE et al. (2020) presentend a new algorithm called Faster-RCNN + MRMnet, that better the detection of stunned chickens with notable precision (98,06 %) and efficiency (43.700 chicken per hour). Using 27.828 images, the experiment showed a significant

improvement in precision, comparing with traditional methods, using a residual module of multilayers (MRM) to detailed removal of characteristics. In spite of the positive points, the experiement upgrade could have been reached through outside validation from different data set to evaluate the model. Besides, future work can conseider to implement n algorith in an intelligent control system to electrical stunning poultry slaughter.

In 2021, two scientific articles that addressed chicken recognition through images were published. The first of these articles was written by (Bao et al., 2021), while the second work was developed by (LI et al., 2021).

The article by (BAO et al., 2021), presented a method to identify dead and sick chickens through artificial intelligence and machine learning algorithms, using rings on the birds' feet and a detection terminal powered by a ZigBee network. The system measured displacement and activity intensity with 95.6% accuracy, reducing manual work and improving efficiency. The cost of the system decreases over time, making it economically superior. The design incorporated data from a cell phone app and rings on the chickens' feet, containing sensors, battery and microprocessor, while the terminal included storage, battery, indicators and wireless transmission. Machine learning was crucial for analyzing data from 40,000 chickens, determining activity status. The architecture encompassed cage detection units equipped with LED indicators for both local and remote monitoring. The main goal was to improve efficiency and reduce costs in large-scale poultry farms, aimed at making the detection method more accurate and economical. However, it is necessary to make improvements in the implementation of the system, focusing on additional research to improve large-scale data analysis.

The article prepared by (LI et al., 2021), presented a new method using artificial intelligence to segment chicken images correctly. The proposed method was called MSAnet, which stands for deep Convolutional Neural Network based on multiscale attention. This

method demonstrated superior performance compared to traditional ways, such as Mask-RCNN and Unet, when segmenting chicken images. This approach can contribute to improving animal welfare by enabling a more detailed analysis of their behavior, movements and social interactions. An area for improvement in this research is the inclusion of a more thorough analysis of the effectiveness and scalability of the proposed method in practical animal monitoring environments. This must consider various conditions, such as lighting variations, scale changes and possible external interference that can affect the accuracy of chicken image segmentation.

In 2022, MA et al., developed a study on how to improve the identification of chicken faces using advanced object detection techniques, such as GAN (Generative Adversarial Network) and MAE (Masked Autoencoder). The objective was to make the process more accurate and faster. The study showed that these models are more efficient than conventional methods in poultry farming, especially in individual chicken management. Among the conventional models, the most widely used include thresholding method, region segmentation and edge detection. The positive results were evidenced by improvements in F1 and mAP scores, which are well-recognized metrics used to evaluate the performance of models in object detection and segmentation tasks in images. The proposed model also stood out for its high accuracy and speed. However, areas for improvement were identified, such as refining the dataset, improving inference speed, exploring age-specific categories, and optimizing for future applications.

The study conducted by XIE & CHANG (2022) presented a method for identifying the behaviors of broiler chickens, using object detection and recurrence-based artificial neural networks (that is, they are capable of remembering and learning patterns in sequences). The YoLov4 object detection model was used to identify specific parts of the chicken, and the construction of a skeleton allowed the extraction of angles for behavior recognition. Six

different broiler behaviors were identified using an LSTM network (positions: standing, walking, eating, resting, feathering and wing flapping). The proposed scheme achieved an average accuracy of 82%, demonstrating promising performance in outdoor environments. The ability to expand the method to detect behaviors in multiple chickens is an advantage. In terms of improvement, advanced techniques in precision and recall of some specific behaviors are suggested, in addition to exploring possible optimizations in detection and recognition algorithms.

The article FANG et al. (2022), addressed the importance of estimating poultry posture to evaluate abnormal behaviors and predict diseases. It's importante to say that the precision in this estimate allows for more efficient management of birds by producers. The paper proposed the use of computer vision technology, specifically a deep neural network technique, to estimate the posture of broiler chickens. The method was compared to other posture detection algorithms such as SSD, YOLOV3, RetinaNet and Faster_R-CNN. he accuracy of the proposed model for estimating the pose of a single broiler chicken was 91.9%. The ability to estimate the position of chickens makes it easier to detect abnormal behavior. The research highlighted improvements in behavior and pose detection, effective development of algorithms for large-scale monitoring, and the application of deep learning techniques in bird management. However, improvements were suggested, such as applying the algorithms in different scenarios and animal breeds, validating on commercial farms and exploring scalability and computational efficiency in future research.

Authors XIE & CHANG (2022) conducted a study proposing a deep learning approach to identify bird behavior through position estimation, detecting different parts of chickens and estimating position angles to accurately infer behavior. Performed in an open-air cage, the method demonstrated promising results for real-time recognition in poultry farming. The research used deep learning to detect parts of the birds, followed by position estimation to

determine the chicken's angles, which were used to infer behavior. The average behavior detection rate reached 43.93%. Although this rate is not excellent, the promising results and plans for future improvements indicate that the proposed method has the capacity for improvement to achieve higher detection rates in the future. However, the study identified challenges in preciselly classifying the left and right feet due to the limitations of the YoLo model in distinguishing these specific parts, resulting in a lower detection rate. For future improvements, it is planned to evaluate the detection performance for similar and hidden parts in chickens, in addition to incorporating a time series detector to improve behavior recognition.

GUO et al. (2022), developed a study that investigated the use of the DenseNet-264 CNN model for recognizing behaviors in broiler chickens at different ages, highlighting high accuracy rates compared to other CNN models. Challenges included inconsistent image sizes, multiple postures, and feeder/drinker interference. DenseNet-264 outperformed models such as ResNet-152, ResNeXt-101, EfficientNet-B4 and ECA-DenseNet-264, exhibiting better performance on diverse datasets of broiler chickens at different growth stages (88.5% accuracy). However, the lack of depth and angular information in data obtained from a single angle was a challenge, resulting in limitations in accurate recognition. Interference, such as background in cropped images, also affected accuracy. The study highlights the need for additional checks in commercial environments for multiposition and multibehavior recognition in broiler chickens. DenseNet-264, especially, shows promise for real-time recognition in commercial environments. Future research could focus on implementing these models in commercial poultry farms, continuously monitoring chicken behavior to improve management practices and decisions in poultry farming.

Still in 2022, authors YANG et al. (2022), developed a deep learning model, called YOLOv5x-hens, based on the advanced YOLOv5 convolutional neural network. The model

was trained with more than 1,000 images and tested with 200, aiming to monitor the behavior of chickens in cage-free facilities. Using statistical analyses, significant differences between predicted and actual numbers of chickens under various conditions were investigated. The results indicated high model evaluation metrics for detecting chickens on the floor of the wood sawdust bed, with emphasis on 95% accuracy after the birds reached 8 weeks of age. However, limitations, such as inaccurate detections in overlapping situations and uneven lighting, were observed. The study established a new deep learning model for monitoring in cage-free facilities for chicken detection, providing a technical basis for the future development of machine vision systems in commercial cage-free environments.

And the last article selected from the Web of Science database, on the recognition of birds, specifically chickens, through images, was the work developed by CUI et al. (2023), this study presented a more efficient way to check the health of broiler chickens. Combining YOLOv5 with the lightweight mobile EMO model, replacing parts of YOLOv5 with the EMO module. This change made the model more efficient. After training, the model identified the health of caged chickens, achieving high recovery rates (95.9%) and accuracy (95.6%). Compared to basic YOLOv5, the average accuracy has been improved by 1.5%, and in relation to YOLOv7 and YOLOv8, it increased by 3.1% and 1.8%, respectively. This approach aimed to facilitate intelligent health detection, reducing manual intervention and costs in broiler farming. But to improve the experiment, it is essential to provide more information about the number of animals used, ensure data transparency and declare possible competing interests.

Perspectives of Systematic Review

When examining the thirteen articles obtained from the 150 records selected in the Web of Science database that address bird recognition through images, is observed the

significant potential of these researches to benefit poultry production, scientific research and the conservation of these birds. However, it is crucial to highlight that many of the methods used face challenges and limitations, with the accuracy of the models varying according to the data, image conditions and application context. Furthermore, collecting and preparing training data can present complexities and require expertise.

The advances achieved in these studies represent an important milestone in the use of bird recognition technologies through images, aiming to improve the management, conservation and well-being of these animals. However, it is critical to recognize that there is still room for improvements in the accuracy, efficiency, and adaptability of these approaches. At the same time, it is crucial to carefully address ethical issues related to the use of technology in monitoring and evaluating animals.

CONCLUSION

The application of bibliometric analysis in this research combines the analysis of scientific records from WoS using neural networks and machine learning to identify birds from images, becoming possible to group researches that stood out in recent years on the subject.

When analyzing the selected articles, it is noted the absence of specific works related to free-range poultry farming, focusing predominantly on industrial poultry farming. This scenario points to a gap in the scientific literature on the application of bird recognition technologies focused on small-scale poultry production, such as free-range poultry farming.

It is crucial to recognize the importance of extending research and development of these technologies to benefit free-range poultry farming, which plays a significant role in diversifying poultry production. By exploring and understanding the specific needs of this sector, we can be promote innovations that contribute to the well-being, efficiency and sustainability of free-range poultry farming, in line with the continuous search for

improvements in bird management and conservation. Therefore, there is a need for future research aimed at applying bird recognition technologies in free-range poultry farming in order to fill this gap in scientific knowledge and provide comprehensive benefits for different modalities of poultry production.

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DECLARATION OF CONFLICT OF INTERESTS

We don't have any conflicts of interest to declare.

AUTHOS CONTRIBUTIONS

All the authors critically reviewed this manuscript and approved the final version.

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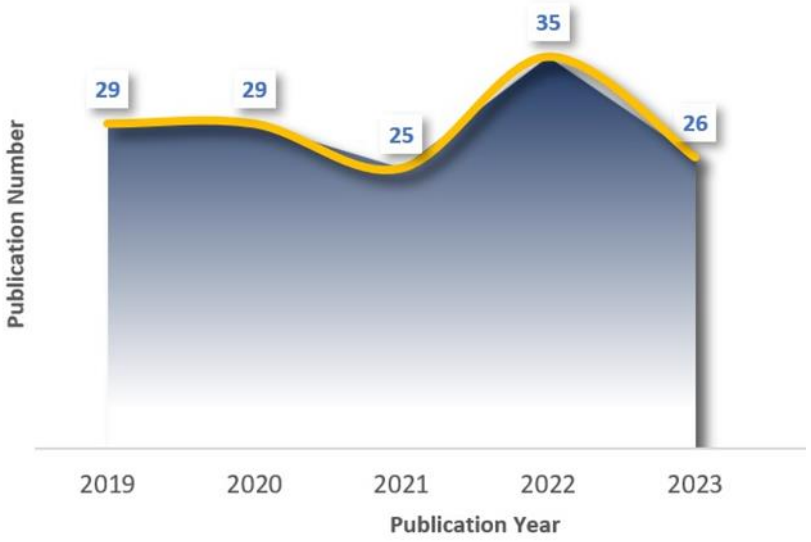
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Graph 1 - Distribution, by year, of publications on bird recognition using neural networks and machine learning.

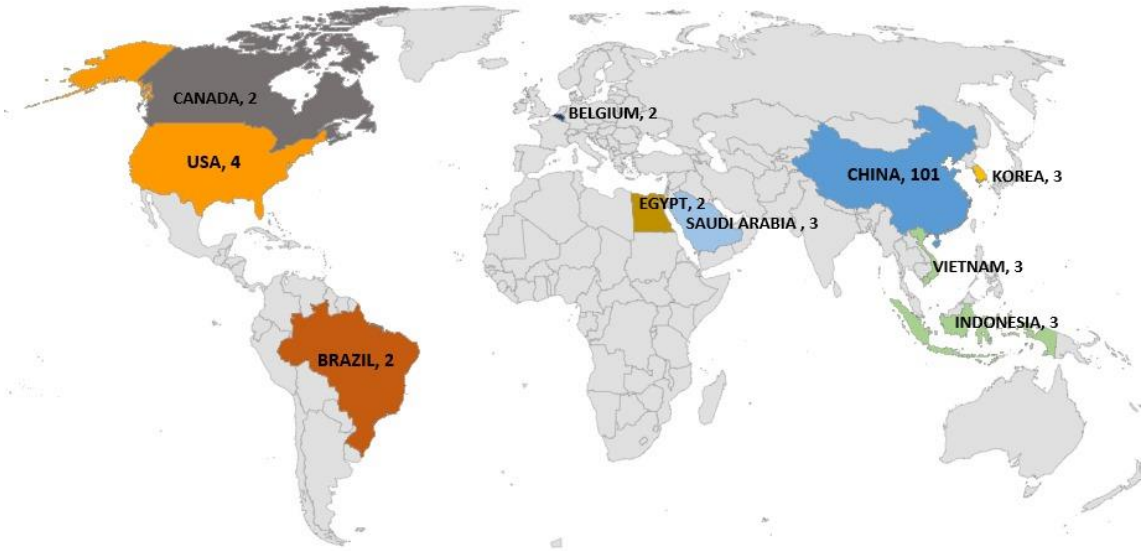


Figure 1 – Number of publications by countries that used neural networks and machine learning for bird recognition and detection.



Figure 2 - List of the 10 journals that published the most on the topic and the number of works published.

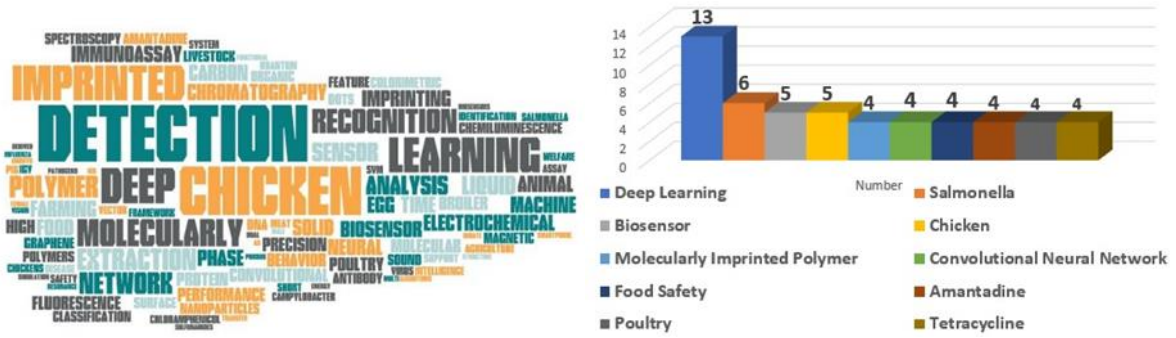


Figure 3 – Cloud of keywords involving bird recognition through neural networks and machine learning with their respective frequencies.

Table 1 - Articles extracted from the Web of Science database.

Title	**Journal**	**Author**	**Year of Publishing**	**Used methods to identification**
Design of Sick Chicken Automatic Detection System Based on Improved Residual Network	IEEE	Haiyang Zhang; Changxi Chen	2020	ResNet
An experimental study of stunned state detection for broiler chickens using an improved convolution neural network algorithm	Computers and Electronics in Agriculture	Chang-Wen Ye; Zhen-Wei Yu; Rui Kang; Khurram Yousaf; Chao Qi; Kun-Jie Chen; Yu-Ping Huang	2020	YOLO + MRM
Real-time behavior detection and judgment of egg breeders based on YOLO v3	Neural Computing and Applications	Juan Wang; Nan Wang; Lihua Li; Zhenhui Ren	2020	YOLOv3
Broiler stunned state detection based on an improved fast region-based convolutional neural network algorithm	Poultry Science	Chang-Wen Ye; Khurram Yousaf; Chao Qi; Chao Liu; Kun-Jie Chen	2020	Faster-RCNN + MRMnet
Detection system of dead and sick chickens in large scale farms based on artificial intelligence	Mathematical Biosciences and Engineering	Yiqin Bao; Hongbing Lu; Qiang Zhao; Zhongxue Yang; Wenbin Xu	2021	Rede ZigBee
Chicken Image Segmentation via Multi-Scale Attention-Based Deep Convolutional Neural Network	IEEE Access	Wei Li; Yang Xiao; Xibin Song; Nalv; Xinbo Jiang; Yan Huang; Jingliang Peng	2021	MSAnet
An Advanced Chicken Face Detection Network Based on GAN and MAE	Animals	Xiaoxiao Ma; Xinai Lu; Yihong Huang; Xinyi Yang; Ziyin Xu; Guozhao Mo; Yufei Ren; Lin Li	2022	GAN; MAE
Behavior Recognition of a Broiler Chicken Using Long Short-Term Memory With Convolution Neural Networks	IEEE Xplore	Bo-Xuan Xie; Chung-Liang Chang	2022	Rede LSTM; YoLov4
Study on Poultry Pose	Animals	Fang C; Zheng H;	2022	Deep Neural

Estimation Based on Multi-Parts Detection		Yang J; Deng T		Network (DNN)
A Deep Learning-Based Posture Estimation Approach for Poultry Behavior Recognition	IEEE Xplore	Bo-Xuan Xie; Chung-Liang Chang	2022	YoLov4
Monitoring Behaviors of Broiler Chickens at Different Ages with Deep Learning	Animals	Yangyang Guo; Samuel E. Aggrey; Peng Wang; Adelumola Oladeinde; Lilong Chai	2022	CNN DenseNet-264
A Deep Learning Model for Detecting Cage-Free Hens on the Litter Floor	Animals	Xiao Yang; Lilong Chai; Ramesh Bahadur Bist; Sachin Subedi; Zihao Wu	2022	YOLOv5x-hens
Research on broiler health status recognition method based on improved YOLOv5	Smart Agricultural Technology	Yue Cui; Xiangchao Kong;, Changxi Chen; Yiwei Li	2023	YOLOv5 + EMO

CAPÍTULO II

Tools to identify Canela-Preta chicken breed by digital images

Tools to identify Canela-Preta chicken breed by digital images

Ferramenta de identificação de galinhas da raça Canela-Preta por meio de imagens digitais

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Highlights

- Detail the app developing process that uses CNNs technology to identify specific characteristics of Canela-Preta breed.
- Captures the images in real time and integration with a server.
- Develops an app using convolutional neural networks (RNCs) to identify Canela-Preta chicken**.**

ABSTRACT

This work was justified by the need to develop an accurate and accessible tool to assist in monitoring and controlling poultry flocks. The main objective of this study was to develop an innovative application, specifically designed to identify Canela-Preta chickens using a smartphone as a platform. The research began with the use of 466 images of 152 Canela - Preta chickens. These images were used to create an identification algorithm. The algorithm architecture was chosen based on experiments and performance evaluations. The YOLO v8 framework and the Random Forest algorithm were used to detect objects and locate chickens in the images. To develop the application, an approach was used where users captured and sent images in real time to a central server and received animal identification results in response. Statistical analysis of the recognition results revealed an average accuracy rate of 99.4% and an average error rate of 0.04%, which highlights the reliability of the approach. The real-time image capture strategy and integration with a central server facilitated the agility of the identification process. The developed application proved to be a promising tool for the accurate and efficient identification of these animals. The findings indicate that the integration of machine learning and image processing technologies can offer innovative solutions to challenges in identifying animals in diverse contexts.

Keywords: bird recognition; computer vision; convolutional neural network.

INTRODUCTION

The practice of free-range chicken raising, shows a productive activity that requires planning and management abilities. An remarkable example is the Canela-Preta chicken, broadly spread in Piauí and Maranhão States. The profound knowledge provides a more efficient production, increasing the productivity and enhancing the opportunities to enter the market. Apart from industrial poultry in terms of production scale and market price, free-range chickens established their presence in the market by competing in flavor and product quality. (Carioca Junior *et al*., 2015).

This method is part of a broader scenario, where in the last decades, the animal production has gone through significant changes driven by the growing demand of sustainable products that promote animal well-being. These changes have strengthened the knowledge areas such as ambience, animal well-being and ethology, conducting installation changes, environment improvements, carrying environmental enrichment practices and management adjustments (Turco, 2019). These advances reflect an ongoing search for more ethical and sustainable practices in animal production, connecting to the relevance of free-range chicken farming as a positive response to these paradigm shifts in agriculture and the food industry.

In the context of these developments, increasing concerns about animal welfare have highlighted the need for less invasive technological tools to collect and analyze data. Non-invasive methods become essential, as they allow reliable information to be obtained without causing stress to the animals. In this sense, these new technologies facilitate the management and measurement of behavioral, physiological and performance indicators, automating data collection and providing support for decision making (Pereira et al., 2015). This interconnection between paradigmatic changes in animal production and the adoption of more ethical technologies highlights the importance of innovative and sustainable approaches to animal husbandry, as we can see in the case of free-range chicken farming.

This study came up in the context of technological advances, where there is a growing demand for effective solutions for identifying animals in different environments. The main goal of this study was to develop a new application, specifically designed to identify Canela Preta chickens using a smartphone as a platform. The convergence between the practical need to monitor poultry flocks and the opportunity offered by the advanced capabilities of convolutional neural networks for identifying patterns in images guided the essence of this study, aiming to contribute significantly to the efficiency and practicality of bird management in several poultry environments.

METHODOLOGY

Ethic certification

This research was approved by the Ethic Commission in Animal Use (Comissão de Ética no Uso de Animais CEUA/UFPI) with registration under Nº 692/2021. It was used Canela-Preta chicken images that belonged to Criatório Familiar Caipira, located in the Assentamento Resistência Camponesa, in the city of Demerval Lobão, rural zone in the state of Piauí.

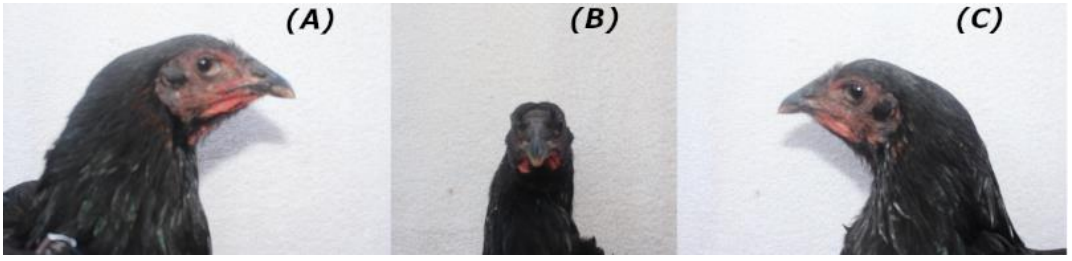
Images acquisition

The original images that formed the database for evaluating the algorithm were used from the work of (Moura, 2022), these images were collected at the Criatório Familiar Caipira, located in the Assentamento Resistência Camponesa, in the city of Demerval Lobão. A total of 466 images of 152 Canela-Preta chickens were used.

The images were captured in three different levels: right lateral plane, frontal plane and left lateral plane. All images have a concentration on the neck part for the chicken's head,

all with the same size in dimension with 1280 height and 1920 width. Figure 1 shows images of a chicken.

Figure 1 - Different image capture plans. (A) right lateral plane, (B) frontal plane and (C) left lateral plane.

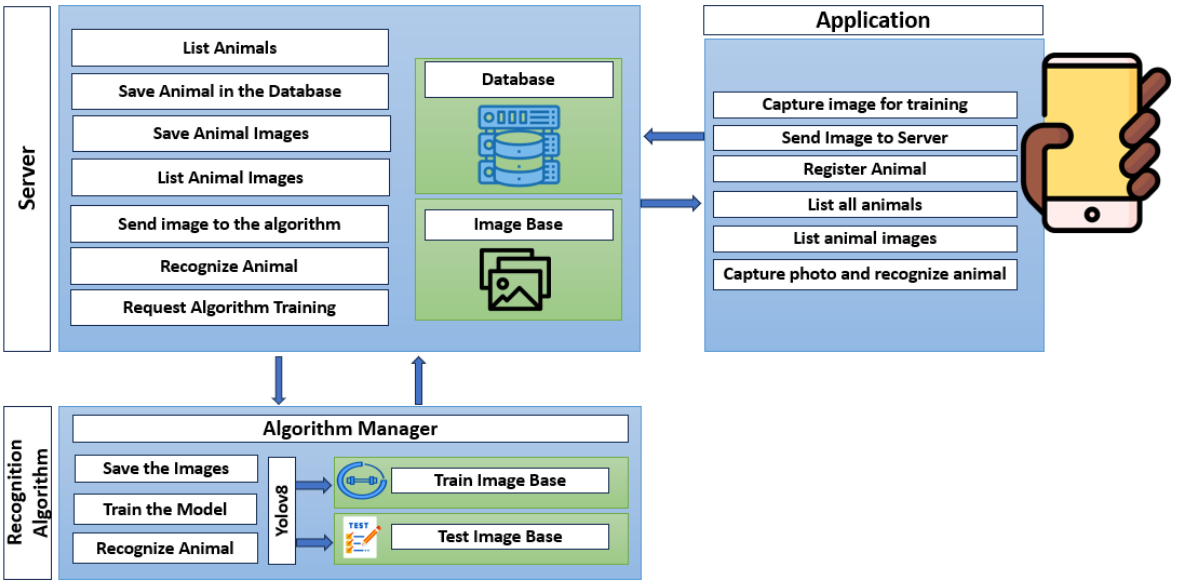


Architecture of the developed tool

Based on the study carried out, an architecture proposal was developed for the developed tool, called AvianIDCP. Firstly, it was necessary to train the model, gathering a set of images of chickens. Each image needed to be labeled to indicate whether or not there was a chicken present, and which part of the image was the chicken. Before sending the images to the machine learning model, it was necessary to create a database of images of 152 black-shin chickens with each animal containing 3 or 4 images. With this, the database totaled a set of 466 images.

The AvianIDCP architecture was composed of three components: the recognition algorithm, which was developed using YOLOv8 and the Random Forest framework; the server, which acted as an intermediary, facilitating communication between the recognition algorithm and the application; and the application, which played the role of capturing and sending photos to the server, presenting the responses to the end user. Figure 2 presents the architecture of the proposed application and the following sections detail each part of this architecture.

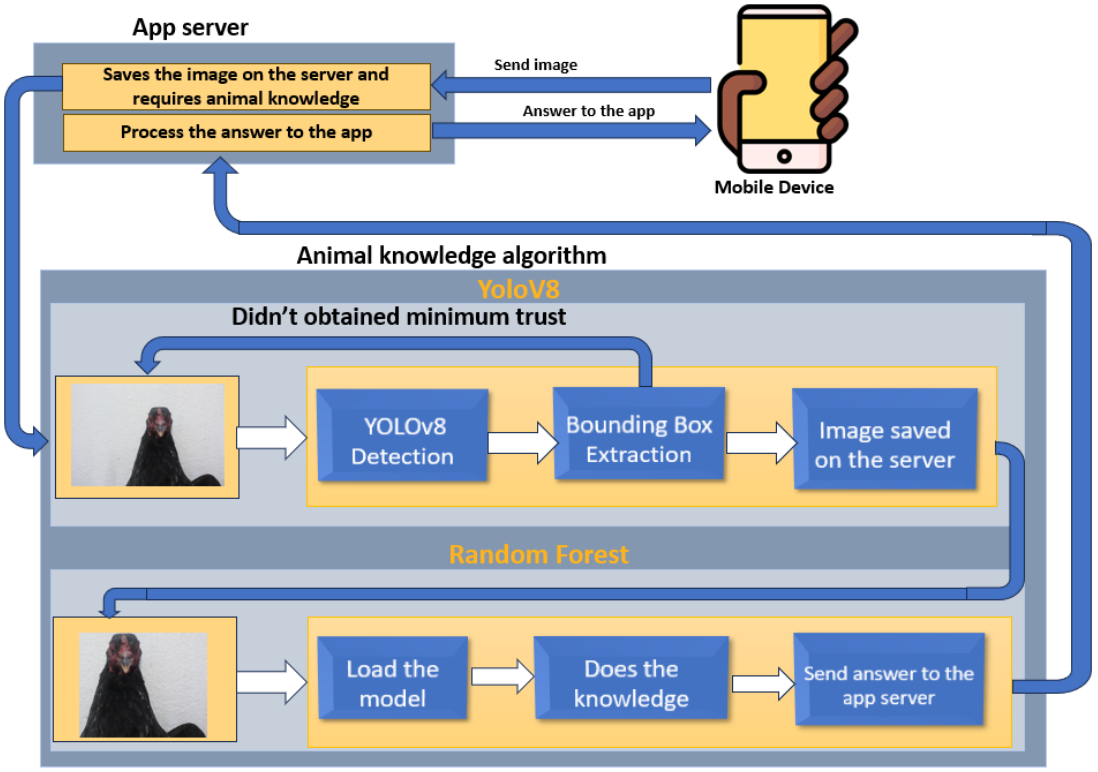
Figure 2 - Architecture of the AvianIDCP tool



Architecture application

The application sends an image to the server app to save the original one, then it sends a request to the animal recognition algorithm for analysis and extraction of the area of interest with the animal identification with Yolov8. If the minimum level of confidence is not obtained, you can repeat the process again, changing to a Yolov8 model that requires a higher processing cost. Then, a second process is necessary where it must recognize the animal with the previously trained model. This server returns a response to the application server, then, it performs the processing and sends the response to the user's application, informing about its identification and an estimate of the probability of matching with that bird, expressed in terms of percentage reliability. Figure 3 shows all the steps taken during this identification.

Figure 3 – Flowchart illustrating the chicken identification process.



Application server

The server manages and stores the data sent by the application for the recognition algorithm. It hosts a set of services that enables the recording of information related to birds, providing a unique identification to each one of them. Among the features offered, the ability to list all registered chickens stands out, displaying their respective names and unique identifiers.

The information relating to a given chicken essentially consists of its name, identification and a collection of associated images. These images are organized based on the identifiers of these chickens and kept in their original form and dimensions as submitted by the app. Additionally, for each image of a chicken, a unique identifier is generated, as well as a link that allows access through the mobile application.

The server, as part of its duties, is responsible for collecting such images and forwarding them to the algorithm, where they are subjected to a series of predetermined operations, according to the logic of the previous section. Furthermore, among the features offered, the option to start the algorithm training process stands out. In this scenario, the server forwards a request so that training can happen based on the images already stored in its repository. It is important to understand that this operation is exclusively triggered by the server, since the training process requires a substantial period of time to complete, becoming available for use only after. The time needed to finish the training is influenced by the number of images previously added to the server. For user awareness, a notification is sent through the mobile application, communicating that this functionality will only be accessible after a certain period has passed.

Mobile Application

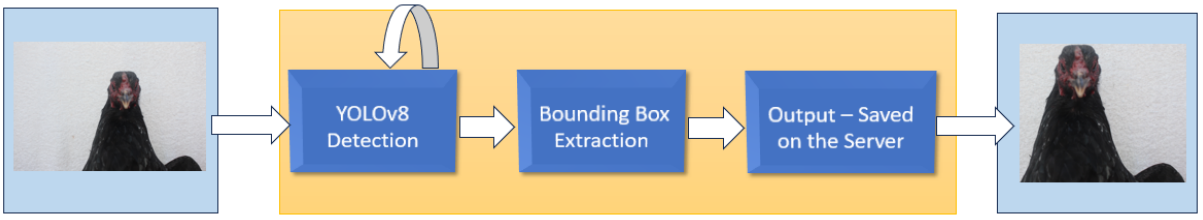
The mobile application was developed using the Flutter framework, created by Google, and the Dart programming language. The choice of this framework is justified by its ability to generate applications compatible with different systems from a single source code.

Yolov8 algorithm for chicken detection

In the process of registering animals through the application, images are captured and sent to the server. The server then processes this image, removing only part of the animal before saving it in the database. For this purpose, version 8 of the YOLO (You Only Look Once) algorithm was used to isolate the relevant portions of the images, specifically the representations of the animals, thus optimizing the training area and focusing exclusively on the regions of interest pertinent to the model in question.

Yolov8 made a cut in the area of interest during training. This step was crucial for the performance of the algorithm, as it made it possible to create the model using only the portion of the image truly relevant for recognizing the animal, as illustrated in Figure 4. In developing the algorithm, optimization was prioritized for an execution that uses as few machine resources as possible since Yolov8 offers five pre-trained detection model options. These models are configured in such a way that, the greater the desired precision, the greater the necessary memory and processing resources used by the server for recognition. In this study, we chose to use the algorithm model with the smallest size and consequently requiring less server processing. However, if the accuracy does not reach the desired level, a new attempt is made using a more accurate Yolov8 model, although this model requires more processing than the first. This approach contributed to the efficiency of the algorithm, since the need to use the model with a higher computational cost in Yolov8 was identified in limited situations. Subsequently, separate images were sent for training and testing.

Figure 4 – Image extraction process using YOLOv8



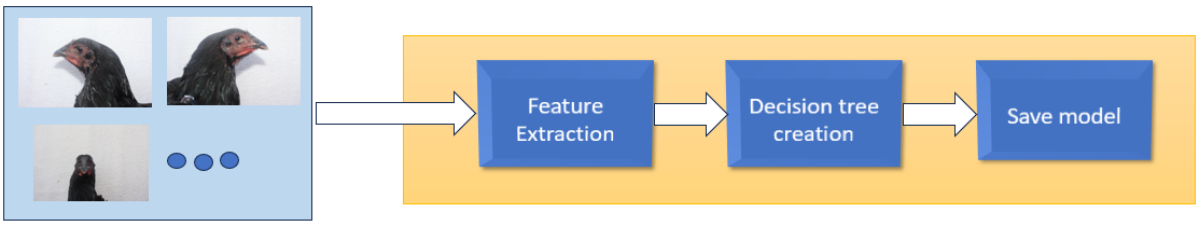
The YOLOv8 algorithm is the most current version and is coordaneted as an independent service, with a manager in charge of supervising the operations made available to the application. These operations include the ability to preserve images, perform model training and perform animal recognition.

Random Forest algorithm built for chicken recognition

The Random Forest algorithm is widely used in machine learning tasks, mainly for classification and regression. For this work, the algorithm was built following the following steps: Data Preparation, Model Construction, Individual Tree Training, Voting and Combination of Results and Model Evaluation. In Data Preparation, the algorithm selects the data for training. This includes collecting a dataset that contains labeled examples, that is, instances with characteristics (attributes) and their respective classes (labels). Data labeling is done by the server before being received by the animal recognition algorithm, where a unique name is assigned to the set of images of a specific animal. This same task is done for all animals.

After cropping the images in the area of interest, using Yolov8, training of the model began using Random Forest. Figure 5 illustrates the process with Random Forest to generate the model.

Figure 5 – Model generator process with Random Forest.



This model can be stored as it specifies the tree depth. In this study, we observed that the image set reached the best results with one hundred trees.

Assessment metrics

Assessment metrics had the purpose of analyze the performance of the algorithm, with the metrics being: accuracy, which measures the precision of the model; and mean absolute error (MAE), a measure that quantifies the average discrepancy between model predictions and actual values.

Accuracy (A)

Accuracy was measured using the number of true positives plus the number of true negatives divided by the total number of elements in the matrix, as described by Carvalho et al. (2011). The Equation is expressed as follows:

$$Accuracy\ (A) = \frac{VP + VN}{VP + VN + FP + FN}$$

which: true positives (VP), samples correctly classified as positive; true negatives (VN), samples correctly classified as negative; false positives (FP); samples incorrectly classified as positive; and false negatives (FN), samples incorrectly classified as negative.

Mean Absolute Error - MAE

Proposed by Sarmento (2006), the mean absolute error of residuals (MAE) was calculated through the sum of the deviations between the observed and estimated weights, divided by the number of observations, as indicated below:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

where: N is the number of images used to observe; yi is the expected value; and ŷi is the prediction value. The smaller the mean absolute error of the residuals, the better the adjusted model.

RESULTS AND ANALYSIS

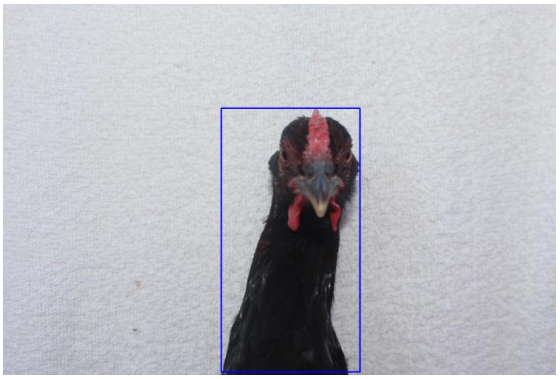
Base images acquisition

The development of the identification algorithm was based on a database composed of 466 images, representing 152 Canela-Preta chickens in their three different planes, according to the proposed methodology. Choosing a diverse and comprehensive database is crucial for training the algorithm, allowing it to effectively recognize different bird shots and perspectives. This approach aims to improve the algorithm's ability to adapt to varying real-world conditions in which images are captured.

Digital image detection and segmentation process

In the identification process, the use of YOLOv8 proved to be an efficient tool, standing out for its inherent speed and accuracy. The use of this object detection model made it possible to extract specific sections in the region of interest in the images, creating a bounding box that precisely delimited the location of the animal (Figure 6). The effectiveness of YOLOv8 is particularly relevant for real-world environments where image capture can be dynamic and variable.

Figure 6 - Image of the chicken with the creation of the bounding box.



The sequential approach adopted in the algorithm is notable, prioritizing the identification of the chicken with a minimum desired reliability. This strategic choice recognizes the inverse relationship between computational cost and process accuracy. In

scenarios where speed in identifying is crucial, such as in the monitoring of poultry flocks, this strategy allows a balance between efficiency and reliability. This chicken identification process was conducted step by step, to achieve a desired result. However, it is essential to recognize that the accuracy of the process can be affected by the computational cost, highlighting the need for adjustments according to the specific requirements of each situation.

By using this approach in several situations, the algorithm demonstrated effectiveness in identifying the regions in which it should create a bounding box. Notably, the algorithm prioritized selecting the animal with the largest bounding box in the image, a crucial feature in scenarios where multiple animals are presented in a single image.

After acquiring the images generated by Yolov8, they were separated for training and testing, marking the beginning of model training with the Random Forest algorithm. This algorithm is especially advantageous in scenarios like the present work, where the data set is relatively small, allowing the generation of a robust model even with a limited number of examples.

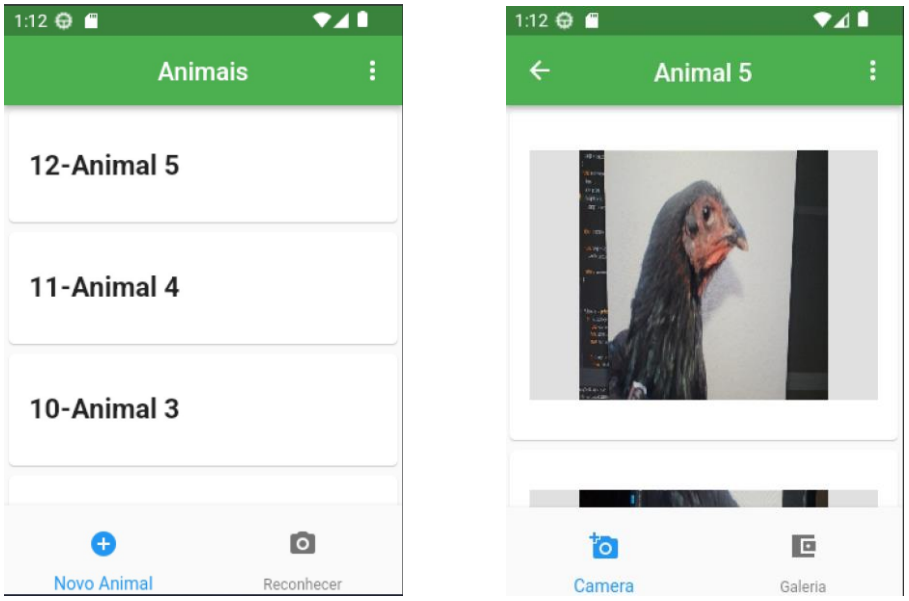
Mobile apps screens

The app, as illustrated in Figure 7-A, presents a list of animals previously registered on the server in its main menu. Each animal is identified and submitted to its respective name. When clicking on an animal's name, the app displays all images associated with that animal, offering the possibility to add new images or delete them (Figure 7-B). The functionality of adding a new image of an animal triggers the user's device camera to capture the image, which is then processed by the app.

During processing, the image is resized to a standard format of 640x640 pixels and adjusted to landscape format if necessary. Furthermore, the application makes use of a cubic interpolation algorithm, aiming to produce an output image with reduced visual artifacts and

improved quality compared to more rudimentary interpolation techniques, such as bilinear interpolation. This provides smaller sized images, capable of efficient storage and processing by both the server and the recognition algorithm.

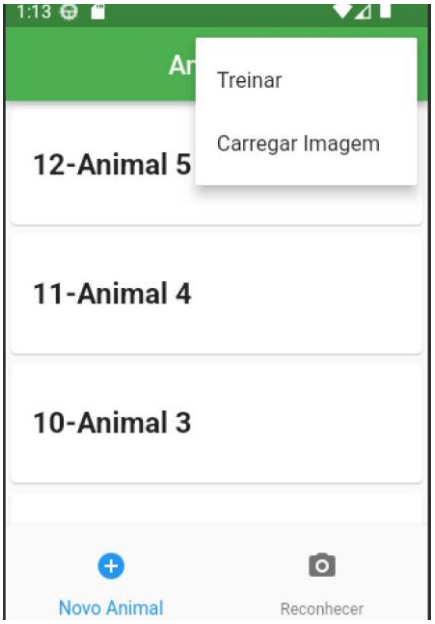
Figure 7 - Mobile app screens.



(A)Screen to list all the images (B) Animal image screen

The inclusion of features such as image loading, artificial intelligence model training and the ability to add new animals highlights the versatility and practicality of the application, as illustrated in Figure 8. These options offer users a range of features to optimize the usage experience and customize the application according to your specific needs.

Figure 8 - Option to train the AI and upload the images to the server.



Requesting images to be loaded into the recognition algorithm indicates an affordable and efficient approach, allowing users to provide a diverse set of images to enhance model training. This characteristic is crucial to ensure the algorithm adapts to different contexts and conditions in which chickens can be captured.

The AI model training option provides an interactive component, allowing users to actively contribute to the continuous improvement of the algorithm. This active participation in model improvement not only increases identification effectiveness but also fosters a sense of involvement on the part of users. When loading a set of images, the user can send an order to perform new training with this new set of images.

The server response, providing the ID of the recognized animal and the associated trust level, adds a layer of transparency and trust to the user. Indication of the level of reliability allows users to assess the certainty of identification, promoting a more informed and conscious use of the application.

Overall, the integration of these apps functionalities demonstrates a comprehensive and user-centered approach, contributing to its usefulness and effectiveness in identifying Canela-Preta chickens.

Machine learning through Random Forests

The test was conducted to determine the average error and accuracy metrics, resulting in an accuracy of 99.04% (Table 1), demonstrating the effectiveness of the model created with the Random Forest algorithm.

The results suggest a consistent correspondence between model predictions and actual data, indicating remarkable accuracy in the process of identifying Canela-Preta chickens. This result is especially significant in image analysis and pattern recognition applications, where reliability in identifying specific patterns is essential.

The accuracy obtained reinforces the effectiveness of the Random Forest model in identifying chickens, providing a solid basis for the practical application of the application in different poultry farming environments.

Table 1 – Identification results of the algorithm created using YOLOv8 and Random Forest.

Images		**Metrics (%)**	
Animals	All the planes	Medium error	Accuracy
152	466	0,04	99,4

The results presented, with an accuracy of 99.4% in correctly identifying images of chickens, indicate good performance in the adopted method. For evaluation, a set of 466 images was used for training and another set of the same 466 for testing. Accuracy is measured by how precisely the chickens were identified, reflecting the effectiveness of the model used in the process. This high hit rate suggests that the method demonstrated an ability to recognize specific characteristics of chickens, overcoming potential challenges related to variations in images, positions or lighting conditions.

Furthermore, the average error rate of just 0.04% highlights the consistency and accuracy of the method in analyzing images. The low average error suggests that incorrect identifications were minimal, showing the robustness of the model in differentiating chickens. This result is crucial, especially in contexts such as monitoring poultry flocks, where precision in individual animal identification is essential to assess their health status, behavior and performance.

Comparing to related works

The methods of this study were compared with existing work in the literature dedicated to identifying birds. Table 2 shows this comparison by displaying the accuracy values and the methods used in the experiments.

Table 2 – Comparison of methods used with related work

Works	**Used learning techniques**	**Accuracy**
Wang *et al.*, (2020)	YOLOv3	92,09%
Ye *et al.*, (2020)	YOLO + MRM	96,77%
Cui *et al.*, (2023)	YOLOv5 + EMO	96,7%.
Proposed Method	**YOLOv8 + *Random Forest***	**99,4%**

The work of Wang et al. (2020), proposed a method to detect and analyze the behavior of laying birds in self-breeding cages using visual images and the YOLO v3 model. The model achieved an accuracy rate of 92.09% in the validation set in recognizing mainly mating behaviors. Additionally, they have developed methods to assess welfare and detect abnormal behavior, which can benefit the poultry industry by raising animal welfare standards.

In the study conducted by Ye et al. (2020), a method was presented to identify the stunning states of broiler chickens in the poultry industry. Using the YOLO convolutional neural network associated with MRM (You Only Look Once + Multilayer Residual Module). The proposed algorithm achieved an accuracy of 96.77% and allowed the detection of a large number of chickens per hour.

The research carried out by Cui et al., (2023), proposed the development and improvement of broiler health detection models using the YOLOv5 network structure associated with EMO (Efficient Multiscale Optimization). The accuracy of the developed model was 96.7%.

The method proposed in this work achieved an accuracy of 99.4% in identifying the Canela-Preta chicken breed. This identification was carried out through the combination of YOLOv8 with the Random Forest algorithm.

The approaches adopted in the research by Wang et al. (2020), Ye et al. (2020) and Cui et al. (2023) share similarities with the method proposed in this work, especially regarding the use of the YOLO algorithm to detect and/or identify birds. However, each of them has different particularities. For example, Wang et al. (2020) exclusively employed the YOLOv3 algorithm for the detection and identification of bird behaviors in self-breeding cages, due to the reliability and effectiveness demonstrated by this deep learning model in identifying bird behaviors such as mating, providing satisfactory and accurate results for the desired application.

Ye et al. (2020) chose to use YOLO associated with MRM due to its ability to learn more refined image features, essential for precise detection tasks, such as identifying the stunning state of chickens. Meanwhile, Cui et al. (2023) chose YOLOv5 in conjunction with EMO, aiming to improve YOLOv5 with modules such as EMO, which reduce computational complexity and model configurations, making it more efficient and suitable

for resource-limited environments, such as mobile devices.

In the method presented in this study, the choice of YOLOv8 was motivated by its significant improvements over previous versions, resulting in superior performance in animal detection, especially small and detailed objects, such as chickens. Furthermore, the use of the Random Forest algorithm proved to be the best option for dealing with smaller data sets, offering accurate results in identifying chickens, even with a limited data set, consisting of only 466 images.

The use of machine learning and deep learning models varies significantly depending on a number of factors, including the type of animal studied, the characteristics of the environment in which they live, the availability of data, and other specific characteristics. For example, different animal species may have unique behavioral patterns and physiology, requiring tailored modeling approaches to capture these nuances. Furthermore, the environment in which animals are monitored can influence the effectiveness of models, as factors such as lighting, noise and weather conditions can affect the quality of the input data.

The quantity and quality of available data also has a crucial role in choosing and training models, as more complex deep learning models may require datasets large enough to effectively generalize relevant patterns and features. Therefore, the selection and adjustment of machine learning and deep learning models must be carefully considered depending on the specific characteristics of the study, the animal in question and the environment in which it is located, aiming to maximize the precision and relevance of the results.

Comparing to studies in the literature, which address birds identification, was essential to contextualize the effectiveness of the proposed model, which demonstrated an accuracy of 99.4% in identifying the Canela-Preta chicken breed. This analysis allowed us

to observe that identifying Canela-Preta chickens was significantly more effective when using the combination of YOLOv8 with the Random Forest algorithm.

CONCLUSION

This chapter presented a solution based in a detailed analyzes and in structuring essential foundations for this project. A comprehensive architecture was developed that comprises three interdependent components, crucial for the effective implementation of the app in question. The first component, called Recognition Algorithm, was built using the Random Forest framework, playing a central role in the system. Its crucial operations include preserving images, training the model, and performing animal recognition. The second component, called Server, plays a crucial role in the architecture, managing and storing the data sent by the app for later use by the Recognition Algorithm. The third component, the App, was developed with the Flutter framework and the Dart language, playing a vital role in interaction with the end user. To conclude, this model offered a solid and consistent structure to successfully implement the app, providing Canela-Preta Chicken recognition by images and allowing an efficient and intuitive user interface.

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CONSIDERAÇÕES FINAIS

O desenvolvimento do sistema móvel para identificação de galinhas da raça canela-preta representa um avanço notável na automatização da fenotipagem em criatórios avícolas. A pesquisa realizou uma análise abrangente das tendências e métodos de processamento de imagem para monitorar e identificar aves na agropecuária, utilizando uma abordagem bibliométrica com a plataforma Web of Science (WoS) e o pacote Bibliometrix do software R, seguida por uma revisão sistemática. Além disso, a aplicação de algoritmos como YOLOv8 e *Random Forest* permitiu a criação de um aplicativo capaz de identificar com precisão as características específicas da raça, com uma taxa média de precisão de 99,4% e taxa de erro médio de 0,04%.

O sistema móvel desenvolvido demonstrou ser uma ferramenta promissora para otimizar o monitoramento e controle de aves, especialmente no estado do Piauí, contribuindo para a eficiência e sustentabilidade da produção avícola. Sua arquitetura oferece uma estrutura sólida e coerente, permitindo o reconhecimento das galinhas da raça Canela-Preta por meio de imagens e fornecendo uma interface de usuário intuitiva e eficiente.

Para futuros trabalhos, podem ser explorados aprimoramentos na arquitetura, incluindo técnicas mais avançadas de aprendizado de máquina, como redes neurais complexas, para elevar ainda mais a precisão do reconhecimento. Além disso, a expansão da plataforma para dispositivos iOS e melhorias na usabilidade do aplicativo são áreas que merecem atenção. Aprofundar estudos de casos específicos de galinhas canela-preta, adaptando o algoritmo para diferentes ambientes, representa uma perspectiva promissora para o desenvolvimento futuro desta inovadora ferramenta na fenotipagem avícola.

APÊNDICES

Resultados obtidos durante o desenvolvimento deste trabalho



CNPA 2023

XVII Congresso Nordestino de Produção Animal

CERTIFICADO

Certificamos que o trabalho intitulado **REDES NEURAIS CONVOLUCIONAIS NO RECONHECIMENTO DE GALINHAS DA RAÇA CANELA-PRETA: DESENVOLVIMENTO DE UM APLICATIVO DE IDENTIFICAÇÃO PARA SMARTPHONE** de autoria de **Raquel Moura Araújo Nolêto; Carleandro de Oliveira Nolêto; Natanael Pereira da Silva Santos**, foi apresentado na sessão de **Pôsteres** durante o **XVII Congresso Nordestino de Produção Animal**, realizado de 29 de novembro a 01 de dezembro de 2023, na cidade de Teresina - PI.

Profa. Dra. Patrícia Guimarães Pimentel
Presidente da SNPA

Prof. Dr. José Lindenberg Rocha Sarmento
Presidente do XVII CNPA

Profa. Dra. Michelle de Oliveira Maia Parente
Coordenadora da Comissão Científica

Promoção Realização Patrocínio Master Patrocínio Apoio Institucional

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SEMANA NACIONAL DE CIÊNCIA E TECNOLOGIA

CERTIFICADO

Certificamos

RAQUEL M.A NOLÊTO, CARLEANDRO NOLÊTO, NATANAEL P.S SANTOS, ALINE M.A MADEIRA

Pela apresentação Artigos - Versão Final: Inovações no Reconhecimento e Detecção de Animais: Uma Análise da Literatura com Ênfase em Redes Neurais e Aprendizado de Máquina. Trabalho apresentado no Encontro Unificado de Computação do Piauí na Semana Nacional de Ciência e Tecnologia: ENUCOMPI / SNCT 2023 em Piripiri, durante o período de 19/10/2023 a 20/10/2023.

Piripiri / Piauí, 20 de outubro de 2023

Mayllon Veras da Silva
Coordenador Local 2023

Ricardo Moura Sekeff Budaruiche
Coordenador Local 2023

Realização: IFPI, UESPI, LAPEC, Universidade Federal do Piauí

Apoio: SBC, FAPEPI, CHRISFAPI

REPÚBLICA FEDERATIVA DO BRASIL
MINISTÉRIO DO DESENVOLVIMENTO, INDÚSTRIA, COMÉRCIO E SERVIÇOS
INSTITUTO NACIONAL DA PROPRIEDADE INDUSTRIAL
DIRETORIA DE PATENTES, PROGRAMAS DE COMPUTADOR E TOPOGRAFIAS DE CIRCUITOS

Certificado de Registro de Programa de Computador

Processo Nº: **BR512023003073-2**

O Instituto Nacional da Propriedade Industrial expede o presente certificado de registro de programa de computador, válido por 50 anos a partir de 1° de janeiro subsequente à data de 09/10/2023, em conformidade com o §2°, art. 2° da Lei 9.609, de 19 de Fevereiro de 1998.

Título: APLICATIVO PARA IDENTIFICAÇÃO DE ANIMAIS

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Linguagem: PYTHON; RUBY

Campo de aplicação: AG-10

Tipo de programa: TC-03; TC-04

Algoritmo hash: SHA-256

Resumo digital hash: 293a3a03205a5e69c0668141fcdb35ca4d8924cbf63dff64621fc3eb3d1111d6

Expedido em: 17/10/2023

Aprovado por:
Carlos Alexandre Fernandes Silva
Chefe da DIPTO