CROP CLASSIFICATION WITH ATTENTION BASED BI-LSTM AND TEMPORAL CONVOLUTION NEURAL NETWORK COMBINATION FOR REMOTE SENSING BREIZHCROP TIME SERIES DATA

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Supervisor: Asst. Prof. Dr. Ahmet COŞKUNÇAY
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ATATURK UNIVERSITY
INSTITUTE OF SCIENCES
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(Uzaktan Algılama Breizhcrop Zaman Serisi Verileri için Dikkat Tabanlı BI-LSTM ve Zamansal Evrişimli Sinir Ağı Kombinasyonu ile Mahsul Sınıflandırması)

MASTER’S THESIS

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CROP CLASSIFICATION WITH ATTENTION BASED BI-LSTM AND TEMPORAL CONVOLUTIONAL NEURAL NETWORK COMBINATION FOR REMOTE SENSING BREIZHCROP TIME SERIES DATA

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Amer Najmualdeen Ali Akbar BANDAR

ABSTRACT

MASTER'S THESIS

CORP CLASSIFICATION WITH ATTENTION BASED BI-LSTM AND TEMPORAL CONVOLUTION NEURAL NETWORK COMBINATION FOR REMOTE SENSING BREIZHCROP TIME SERIES DATA

Amer Najmualdeen Ali Akbar BANDAR

Supervisor: Asst. Prof. Dr. Ahmet COŞKUNÇAY

Purpose: In the contemporary era, remote sensing data have proven to be highly valuable for identifying land use and cover requirements. These data are applicable in various fields, such as crop classification. By collecting remote sensing data for a particular region over a period, we can gain a deeper insight through the analysis of this time series data.

Method: An example of such data is the Breizhcrop dataset, compiled from satellite images taken by Sentinel-2 over time. This research focuses on a neural network that integrates attention mechanisms with a BI-LSTM layer and Temporal-CNN for crop classification. Two distinct approaches were employed: one utilizing the entire dataset and the other using class-balanced data.

Findings: By employing the designed neural network, the attention mechanism was used to capture local features, while a second layer identified general features. In the first approach, which used the entire dataset, the model achieved an accuracy of 82%. In the second approach, where the data were balanced according to class counts, the accuracy improved to 86%.

Results: The neural network was tested on the BreizhCrop dataset, and the findings indicate that it outperforms alternative methods. The results demonstrate that balancing the data based on class counts significantly enhances the model's accuracy.

Keywords: Land use and coverage, Attention mechanism, Crop classification, Remote sensing, Time series

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ÖZET

YÜKSEK LİSANS TEZİ

UZAKTAN ALGILAMA BREIZHCROP ZAMAN SERİSİ VERİLERİ İÇİN DİKKAT TABANLI BI-LSTM VE ZAMANSAL EVRİŞİMLİ SİNİR AĞI KOMBİNASYONU İLE MAHSUL SINIFLANDIRMASI

Amer Najmualdeen Ali Akbar BANDAR

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Amaç: Modern çağda, uzaktan algılama verileri, arazi kullanımını ve örtü ihtiyaçlarını belirlemek için son derece değerli olduğunu kanıtlamıştır. Bu veriler, mahsul sınıflandırması gibi çeşitli alanlarda uygulanabilir. Belirli bir bölge için zamanla uzaktan algılama verilerini toplayarak, bu zaman serisi verilerin analizi ile daha derin bir anlayış elde edebiliriz.

Yöntem: Bu tür verilerin bir örneği, zamanla Sentinel-2 tarafından çekilen uydu görüntülerinden derlenen Breizhcrop veri setidir. Bu araştırma, mahsul sınıflandırması için BI-LSTM katmanı ve Zamansal-CNN ile dikkat mekanizmalarını entegre eden bir sinir ağına odaklanmaktadır. İki farklı yaklaşım kullanılmıştır: biri tüm veri setini kullanarak, diğeri ise sınıf dengeli veriler kullanarak.

Bulgular: Tasarlanan sinir ağını kullanarak, dikkat mekanizması yerel özellikleri yakalamak için, ikinci katman ise genel özellikleri belirlemek için kullanılmıştır. Tüm veri setinin kullanıldığı ilk yaklaşımda model, %82 doğruluk elde etmiştir. Verilerin sınıf sayısına göre dengelendiği ikinci yaklaşımda ise doğruluk %86'ya yükselmiştir.

Sonuç: Sinir ağı, BreizhCrop veri seti üzerinde test edilmiş ve bulgular, alternatif yöntemlerden daha iyi performans gösterdiğini ortaya koymuştur. Sonuçlar, verilerin sınıf sayılarına göre dengelenmesinin modelin doğruluğunu önemli ölçüde artırdığını göstermektedir.

Anahtar Kelimeler: Arazi kullanımı ve örtüsü, Dikkat mekanizması, Ürün sınıflandırması, Uzaktan algılama, Zaman serisi

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GENİŞLETİLMİŞ ÖZET

Uzaktan algılama, modern tarım, çevresel izleme ve arazi yönetiminde vazgeçilmez bir araç haline gelmiştir. Sensörler aracılığıyla uydu veya uçaklardan Dünya yüzeyine ait verilerin toplanması işlemi, çeşitli uygulamalar için değerli bilgiler sunar. Bu teknolojinin en önemli kullanım alanlarından biri mahsul sınıflandırmasıdır. Uydu görüntüleri analiz edilerek farklı bitki türleri belirlenebilir, mahsul sağlığı izlenebilir, verim tahminleri yapılabilir ve çevresel faktörlerin bitki büyümesi üzerindeki etkileri değerlendirilebilir.

Mahsul sınıflandırması, tarım yönetimi ve çevresel sürdürülebilirlik açısından kritik öneme sahiptir. Tarım alanlarının etkin yönetimi, ürün verimliliğinin artırılması ve doğal kaynakların korunması için doğru ve güncel bilgiye ihtiyaç duyulmaktadır. Uydu görüntüleri, geniş alanları kapsayan ve zaman içinde sürekli olarak güncellenen veriler sunduğu için bu tür bilgiler sağlar. Bu veriler, bitki örtüsünün spektral özelliklerini analiz ederek farklı bitki türlerini ayırt etmeye yardımcı olur. Özellikle Sentinel-2 gibi uydu verileri, görünürden kısa dalga kızılötesine kadar 13 spektral bantta yüksek çözünürlüklü optik görüntüler sağlar. Bu görüntüler, bitkilerin spektral özellikleri hakkında detaylı bilgi sunar ve farklı bitki türlerini ayırt etmeye yardımcı olur. Ancak, bu verilerin analizinde zaman serisi verilerinin ileri düzeyde yorumlanması ve dengesiz veri sınıfları gibi zorluklar bulunur. Bu sorunların üstesinden gelmek için özellikle dikkat mekanizmaları ve LSTM (Uzun Kısa Vadeli Bellek) ağları gibi derin öğrenme teknikleri umut verici çözümler sunmaktadır. Uzaktan algılama verilerinin kullanımı, sadece tarım alanlarının izlenmesi ve yönetimi için değil, aynı zamanda çevresel değişimlerin izlenmesi, doğal afetlerin takibi ve ekosistemlerin korunması gibi birçok farklı alanda da büyük önem taşımaktadır. Örneğin, orman yangınları, sel felaketleri ve kuraklık gibi doğal afetlerin etkilerinin hızlı bir şekilde değerlendirilmesi ve bu olaylara yönelik önlemlerin alınması, uzaktan algılama verileri sayesinde mümkün olmaktadır. Ayrıca, iklim değişikliği gibi uzun vadeli çevresel değişimlerin izlenmesi ve bu değişimlerin ekosistemler üzerindeki etkilerinin anlaşılması da uzaktan algılama teknolojileri ile sağlanabilir.

Bu çalışma, Dikkat Tabanlı Bi-LSTM (Çift Yönlü Uzun Kısa Vadeli Bellek) ve Zamansal Evrişimli Sinir Ağları (TCNN) kombinasyonunu kullanarak mahsul sınıflandırma doğruluğunu artırmayı amaçlamaktadır. Önerilen yöntem, zaman serisi uzaktan algılama verilerinden önemli özellikleri daha iyi yakalamak için dikkat mekanizmalarını içermektedir. Araştırmanın ana katkıları şunlardır: Bi-LSTM ve TCNN'yi birleştiren hibrit bir sinir ağı modeli geliştirmek, dikkat mekanizmalarını kullanarak zaman serisi verilerden özellik çıkarımını iyileştirmek ve veri kümesindeki sınıf dengesizliklerini ele alarak model doğruluğunu artırmak. Bu çalışma, tarım yönetimi ve çevresel izleme alanlarında önemli katkılar sunmaktadır. Dikkat tabanlı derin öğrenme tekniklerinin kullanılması, veri setlerindeki dengesizlikleri gidermeye yardımcı olarak sınıflandırma doğruluğunu artırmaktadır. Ayrıca, zaman serisi verilerinin analizi, bitki örtüsünün zaman içindeki değişimlerini daha iyi anlamamıza olanak tanır. Bu, tarım alanlarının daha etkin bir şekilde yönetilmesine ve çevresel sürdürülebilirliğin sağlanmasına katkıda bulunur.

Çalışmada kullanılan veri kümesi, Sentinel-2 uydu görüntülerinden elde edilen zaman serisi verilerini içeren BreizhCrops veri kümesidir. Veri kümesi, sınıf dağılımlarını dengelemek için ön işleme tabi tutulmuş ve model çeşitli performans metrikleri kullanılarak eğitilmiş ve değerlendirilmiştir. Dikkat tabanlı ve evrişimli sinir ağları, zaman serisi verilerden yerel ve genel özellikleri çıkarmak için kullanılmıştır. İki farklı yaklaşım uygulanmıştır: biri tüm veri setini kullanırken, diğeri sınıf sayılarına göre dengeli verileri kullanmıştır. İlk yaklaşımda model %82'lik bir doğruluk oranına ulaşırken, dengeli veri kullanılarak %86'lık bir doğruluk oranı elde edilmiştir.

Veri kümesinin ön işleme aşamasında, verilerin normalize edilmesi, eksik verilerin doldurulması ve outlier'ların (aykırı değerlerin) tespit edilip düzeltilmesi gibi işlemler yapılmıştır. Bu aşamalar, modelin eğitim sürecinde daha iyi performans göstermesini sağlamak için kritik öneme sahiptir. Ayrıca, veri kümesindeki sınıf dengesizliklerini gidermek için çeşitli teknikler kullanılmıştır. Örneğin, azınlık sınıflarının temsil edilme oranını artırmak için veri artırma (data augmentation) teknikleri uygulanmıştır. Bu teknikler, modelin tüm sınıfları daha iyi öğrenmesini sağlar ve genel performansı artırır.

Sinir ağı modelleri, eğitilirken dikkat mekanizmaları ve evrişimli katmanlar kullanılmıştır. Modelin performansı, doğruluk, kesinlik, hatırlama, F1 skoru ve kappa skoru gibi metriklerle değerlendirilmiştir. Elde edilen sonuçlar, önerilen yöntemin mevcut yaklaşımlardan daha üstün olduğunu göstermektedir. Modelin eğitimi sırasında, öğrenme oranı, epoch sayısı ve batch size gibi hiperparametreler optimize edilmiştir. Bu, modelin daha hızlı ve etkili bir şekilde öğrenmesini sağlar.

Dikkat mekanizmaları, zaman serisi verilerinden önemli özelliklerin çıkarılmasında büyük bir rol oynamaktadır. Bu mekanizmalar, ağın en önemli verilere odaklanmasını sağlayarak gereksiz bilgileri filtreler. Dikkat tabanlı modeller, değişken uzunluktaki giriş verileriyle başa çıkmada ve belirli görevler için en alakalı kısımlara odaklanmada etkilidir. Dikkat mekanizmaları, özellikle zaman serisi verilerinin analizinde büyük avantajlar sunar. Bu mekanizmalar, modelin geçmiş verilerdeki önemli anları tanımasını ve bu anlara odaklanmasını sağlar. Bu, modelin daha doğru ve hassas tahminler yapmasına olanak tanır. Ayrıca, dikkat mekanizmaları, modelin karmaşık veri yapılarıyla başa çıkmasını kolaylaştırır ve verilerin daha etkili bir şekilde işlenmesini sağlar. Dikkat mekanizmalarının en önemli avantajlarından biri, modelin dikkatini belirli zaman dilimlerine veya veri noktalarına odaklayabilmesidir. Bu, özellikle tarım ve çevre yönetimi gibi alanlarda büyük bir avantaj sağlar, çünkü bu alanlardaki veriler genellikle zaman içinde değişen ve karmaşık yapıdadır. Dikkat mekanizmaları, bu tür verilerin analizinde büyük bir hassasiyet sağlar ve modelin performansını artırır.

Bu çalışma, önerilen sinir ağının alternatif yaklaşımlardan daha iyi performans gösterdiğini ve sınıf sayılarına göre dengelenen verilerin model doğruluğunu önemli ölçüde artırdığını göstermektedir. Mahsul sınıflandırma görevinde dikkat mekanizmalarının ve derin öğrenme tekniklerinin etkinliği vurgulanmıştır. Elde edilen bulgular, tarım alanlarının daha etkin bir şekilde yönetilmesine katkıda bulunacak önemli bilgiler sunmaktadır. Özellikle, verilerin zaman serisi olarak analiz edilmesi, bitki örtüsünün zaman içindeki değişimlerini daha iyi anlamamıza olanak tanır. Bu, tarım alanlarının verimliliğini artırmak ve çevresel sürdürülebilirliği sağlamak için önemli bir adımdır.

Bu çalışmanın sonuçları, dikkat mekanizmaları ve derin öğrenme tekniklerinin uzaktan algılama verileriyle mahsul sınıflandırmasında başarılı olduğunu göstermektedir. Gelecekte, farklı veri kümeleri ve yöntemler kullanılarak bu yaklaşımın daha da geliştirilmesi ve uygulanması önerilmektedir. Ayrıca, sınıf dengesizliklerini gidermek için veri artırma ve diğer ön işleme tekniklerinin daha kapsamlı bir şekilde incelenmesi faydalı olacaktır. Gelecek araştırmalar için öneriler arasında, farklı uydu verilerinin kullanılması ve daha geniş veri setlerinin incelenmesi bulunmaktadır. Ayrıca, farklı derin öğrenme tekniklerinin ve dikkat mekanizmalarının birleştirilerek daha karmaşık ve hassas modellerin geliştirilmesi önerilmektedir. Bu, tarım alanlarının daha etkin bir şekilde yönetilmesine ve çevresel sürdürülebilirliğin sağlanmasına katkıda bulunacaktır.

Bu genişletilmiş özet, tezin ana hatlarını ve önemli bulgularını özetlemekte ve gelecekteki araştırmalar için öneriler sunmaktadır. Dikkat mekanizmaları ve derin öğrenme tekniklerinin etkinliği vurgulanarak, bu yöntemlerin tarım ve arazi yönetimindeki potansiyeli ortaya konmuştur.

Uzaktan algılama ve mahsul sınıflandırması konusundaki literatür, bu alandaki gelişmeleri ve uygulamaları kapsamlı bir şekilde incelemektedir. Literatürde, uzaktan algılama verilerinin tarım ve çevre yönetiminde nasıl kullanıldığına dair çeşitli çalışmalar bulunmaktadır. Bu çalışmalar, uydu görüntülerinin analizi, zaman serisi verilerinin yorumlanması ve derin öğrenme tekniklerinin uygulamaları gibi konuları içermektedir. Literatürde, özellikle Sentinel-2 uydu verilerinin kullanımı üzerinde durulmaktadır. Sentinel-2, yüksek çözünürlüklü optik görüntüler sağlayarak tarım alanlarının detaylı bir şekilde analiz edilmesine olanak tanır. Ayrıca, zaman serisi verilerinin analizi, bitki örtüsünün zaman içindeki değişimlerini izlemek için önemli bir araçtır. Bu veriler, tarım alanlarının verimliliğini artırmak ve çevresel sürdürülebilirliği sağlamak için kritik öneme sahiptir. Dikkat mekanizmaları ve derin öğrenme teknikleri, literatürde sıkça tartışılan konular arasındadır. Bu teknikler, uzaktan algılama verilerinin daha hassas ve doğru bir şekilde analiz edilmesine olanak tanır. Literatürde, bu tekniklerin tarım ve çevre yönetiminde nasıl uygulandığına dair çeşitli örnekler bulunmaktadır. Bu çalışmalar, tarım alanlarının etkin yönetimi ve çevresel sürdürülebilirliğin sağlanması açısından önemli bilgiler sunmaktadır.

Önerilen model, Dikkat Tabanlı Bi-LSTM ve TCNN'nin kombinasyonunu içermektedir. Bi-LSTM, verilerin çift yönlü olarak işlenmesini sağlar, bu da zaman serisi verilerinde hem geçmiş hem de gelecekteki bilgilerin kullanılmasını mümkün kılar. TCNN ise zaman serisi verilerinin yerel özelliklerini çıkarır. Bu iki tekniğin birleşimi, modelin genel performansını artırır ve verilerin daha hassas bir şekilde analiz edilmesini sağlar. Dikkat mekanizmaları, modelin belirli veri noktalarına veya zaman dilimlerine odaklanmasını sağlar. Bu, özellikle zaman serisi verilerinin analizinde büyük bir avantajdır çünkü bu veriler genellikle zaman içinde değişen ve karmaşık yapıdadır. Dikkat mekanizmaları, modelin bu tür verilerin en önemli kısımlarına odaklanmasını sağlar ve gereksiz bilgileri filtreler. Bu, modelin daha hassas ve doğru tahminler yapmasına olanak tanır. Modelin eğitim sürecinde kullanılan hiperparametreler, modelin performansını önemli ölçüde etkiler. Bu çalışmada, öğrenme oranı, epoch sayısı ve batch size gibi hiperparametreler optimize edilmiştir. Bu, modelin daha hızlı ve etkili bir şekilde öğrenmesini sağlar. Ayrıca, veri artırma teknikleri kullanılarak veri kümesindeki dengesizlikler giderilmiştir. Bu teknikler, modelin tüm sınıfları daha iyi öğrenmesini sağlar ve genel performansı artırır.

Elde edilen bulgular, modelin mevcut yaklaşımlardan daha üstün olduğunu göstermektedir. Modelin doğruluk, kesinlik, hatırlama, F1 skoru ve kappa skoru gibi metriklerde yüksek performans sergilediği görülmüştür. Bu, modelin genel performansını ve sınıflandırma doğruluğunu artırdığını göstermektedir. Modelin yüksek performans göstermesi, tarım alanlarının daha etkin bir şekilde yönetilmesine ve çevresel sürdürülebilirliğin sağlanmasına katkıda bulunur. Özellikle, zaman serisi verilerinin analizi, bitki örtüsünün zaman içindeki değişimlerini daha iyi anlamamıza olanak tanır. Bu, tarım alanlarının verimliliğini artırmak ve çevresel sürdürülebilirliği sağlamak için önemli bir adımdır.

Bu çalışmanın sonuçları, dikkat mekanizmaları ve derin öğrenme tekniklerinin uzaktan algılama verileriyle mahsul sınıflandırmasında başarılı olduğunu göstermektedir. Gelecekte, farklı veri kümeleri ve yöntemler kullanılarak bu yaklaşımın daha da geliştirilmesi ve uygulanması önerilmektedir. Ayrıca, sınıf dengesizliklerini gidermek için veri artırma ve diğer ön işleme tekniklerinin daha kapsamlı bir şekilde incelenmesi faydalı olacaktır. Gelecek araştırmalar için öneriler arasında, farklı uydu verilerinin kullanılması ve daha geniş veri setlerinin incelenmesi bulunmaktadır. Örneğin, farklı uydu sensörlerinden elde edilen verilerin birleştirilmesi, modelin performansını artırabilir. Ayrıca, farklı derin öğrenme tekniklerinin ve dikkat mekanizmalarının birleştirilerek daha karmaşık ve hassas modellerin geliştirilmesi önerilmektedir. Bu, tarım alanlarının daha etkin bir şekilde yönetilmesine ve çevresel sürdürülebilirliğin sağlanmasına katkıda bulunacaktır.

Bu genişletilmiş özet, tezin ana hatlarını ve önemli bulgularını özetlemekte ve gelecekteki araştırmalar için öneriler sunmaktadır. Dikkat mekanizmaları ve derin öğrenme tekniklerinin etkinliği vurgulanarak, bu yöntemlerin tarım ve arazi yönetimindeki potansiyeli ortaya konmuştur. Uzaktan algılama ve mahsul sınıflandırması konusundaki literatür, bu alandaki gelişmeleri ve uygulamaları kapsamlı bir şekilde incelemektedir. Literatürde, uzaktan algılama verilerinin tarım ve çevre yönetiminde nasıl kullanıldığına dair çeşitli çalışmalar bulunmaktadır. Bu çalışmalar, uydu görüntülerinin analizi, zaman serisi verilerinin yorumlanması ve derin öğrenme tekniklerinin uygulamaları gibi konuları içermektedir. Literatürde, özellikle Sentinel-2 uydu verilerinin kullanımı üzerinde durulmaktadır. Sentinel-2, yüksek çözünürlüklü optik görüntüler sağlayarak tarım alanlarının detaylı bir şekilde analiz edilmesine olanak tanır. Ayrıca, zaman serisi verilerinin analizi, bitki örtüsünün zaman içindeki değişimlerini izlemek için önemli bir araçtır. Bu veriler, tarım alanlarının verimliliğini artırmak ve çevresel sürdürülebilirliği sağlamak için kritik öneme sahiptir. Dikkat mekanizmaları ve derin öğrenme teknikleri, literatürde sıkça tartışılan konular arasındadır. Bu teknikler, uzaktan algılama verilerinin daha hassas ve doğru bir şekilde analiz edilmesine olanak tanır. Literatürde, bu tekniklerin tarım ve çevre yönetiminde nasıl uygulandığına dair çeşitli örnekler bulunmaktadır. Bu çalışmalar, tarım alanlarının etkin yönetimi ve çevresel sürdürülebilirliğin sağlanması açısından önemli bilgiler sunmaktadır.

Derin öğrenme teknikleri, büyük veri kümelerinin analizinde ve karmaşık veri yapılarını anlamada büyük avantajlar sunar. Bu teknikler, özellikle zaman serisi verilerinin analizinde etkili bir şekilde kullanılabilir. Zaman serisi verileri, belirli bir zaman diliminde toplanan ve zaman içindeki değişimleri gösteren verilerdir. Tarım ve çevre yönetimi gibi alanlarda, bu veriler, bitki örtüsünün zaman içindeki değişimlerini izlemek ve bu değişimlerin nedenlerini anlamak için kullanılır. Derin öğrenme teknikleri, zaman serisi verilerinin analizinde büyük avantajlar sunar. Bu teknikler, verilerin daha hassas ve doğru bir şekilde analiz edilmesine olanak tanır. Örneğin, LSTM ağları, uzun vadeli bağımlılıkları öğrenmek için özel olarak tasarlanmış bir tür tekrarlayan sinir ağıdır. Bu ağlar, zaman serisi verilerindeki uzun vadeli bağımlılıkları öğrenmede ve tahmin yapmada büyük bir hassasiyet sağlar. Ayrıca, CNN'ler, verilerdeki yerel özellikleri çıkarma konusunda büyük bir avantaj sağlar. Bu iki tekniğin birleşimi, modelin genel performansını artırır ve sınıflandırma görevlerinde daha iyi sonuçlar elde edilmesini sağlar.

Modelin performansı, çeşitli metrikler kullanılarak değerlendirilmiştir. Bu metrikler arasında doğruluk, kesinlik, hatırlama, F1 skoru ve kappa skoru bulunmaktadır. Doğruluk, modelin doğru tahmin ettiği örneklerin toplam örneklere oranını gösterir. Kesinlik, modelin pozitif olarak tahmin ettiği örneklerin gerçekten pozitif olma oranını gösterir. Hatırlama, gerçek pozitif örneklerin model tarafından ne kadarının doğru tahmin edildiğini gösterir. F1 skoru, kesinlik ve hatırlamanın harmonik ortalamasıdır ve modelin genel performansını gösterir. Kappa skoru ise modelin rastgele tahminlerden ne kadar daha iyi olduğunu gösterir. Bu metrikler kullanılarak yapılan değerlendirmeler, önerilen yöntemin mevcut yaklaşımlardan daha üstün olduğunu göstermektedir. Modelin doğruluk, kesinlik, hatırlama ve F1 skoru gibi metriklerde yüksek performans sergilediği görülmüştür. Ayrıca, kappa skoru da modelin rastgele tahminlerden önemli ölçüde daha iyi olduğunu göstermektedir. Bu, modelin genel performansını ve sınıflandırma doğruluğunu artırdığını göstermektedir.

Bu çalışmanın sonuçları, dikkat mekanizmaları ve derin öğrenme tekniklerinin uzaktan algılama verileriyle mahsul sınıflandırmasında başarılı olduğunu göstermektedir. Gelecekte, farklı veri kümeleri ve yöntemler kullanılarak bu yaklaşımın daha da geliştirilmesi ve uygulanması önerilmektedir. Ayrıca, sınıf dengesizliklerini gidermek için veri artırma ve diğer ön işleme tekniklerinin daha kapsamlı bir şekilde incelenmesi faydalı olacaktır. Gelecek araştırmalar için öneriler arasında, farklı uydu verilerinin kullanılması ve daha geniş veri setlerinin incelenmesi bulunmaktadır. Ayrıca, farklı derin öğrenme tekniklerinin ve dikkat mekanizmalarının birleştirilerek daha karmaşık ve hassas modellerin geliştirilmesi önerilmektedir. Bu, tarım alanlarının daha etkin bir şekilde yönetilmesine ve çevresel sürdürülebilirliğin sağlanmasına katkıda bulunacaktır. Bu genişletilmiş özet, tezin ana hatlarını ve önemli bulgularını özetlemekte ve gelecekteki araştırmalar için öneriler sunmaktadır. Dikkat mekanizmaları ve derin öğrenme tekniklerinin etkinliği vurgulanarak, bu yöntemlerin tarım ve arazi yönetimindeki potansiyeli ortaya konmuştur. Uzaktan algılama ve mahsul sınıflandırması konusundaki literatür, bu alandaki gelişmeleri ve uygulamaları kapsamlı bir şekilde incelemektedir. Literatürde, uzaktan algılama verilerinin tarım ve çevre yönetiminde nasıl kullanıldığına dair çeşitli çalışmalar bulunmaktadır. Bu çalışmalar, uydu görüntülerinin analizi, zaman serisi verilerinin yorumlanması ve derin öğrenme tekniklerinin uygulamaları gibi konuları içermektedir. Literatürde, özellikle Sentinel-2 uydu verilerinin kullanımı üzerinde durulmaktadır. Sentinel-2, yüksek çözünürlüklü optik görüntüler sağlayarak tarım alanlarının detaylı bir şekilde analiz edilmesine olanak tanır. Ayrıca, zaman serisi verilerinin analizi, bitki örtüsünün zaman içindeki değişimlerini izlemek için önemli bir araçtır. Bu veriler, tarım alanlarının verimliliğini artırmak ve çevresel sürdürülebilirliği sağlamak için kritik öneme sahiptir. Dikkat mekanizmaları ve derin öğrenme teknikleri, literatürde sıkça tartışılan konular arasındadır. Bu teknikler, uzaktan algılama verilerinin daha hassas ve doğru bir şekilde analiz edilmesine olanak tanır. Literatürde, bu tekniklerin tarım ve çevre yönetiminde nasıl uygulandığına dair çeşitli örnekler bulunmaktadır. Bu çalışmalar, tarım alanlarının etkin yönetimi ve çevresel sürdürülebilirliğin sağlanması açısından önemli bilgiler sunmaktadır.

Bu genişletilmiş özet, tezin ana hatlarını ve önemli bulgularını özetlemekte ve gelecekteki araştırmalar için öneriler sunmaktadır. Dikkat mekanizmaları ve derin öğrenme tekniklerinin etkinliği vurgulanarak, bu yöntemlerin tarım ve arazi yönetimindeki potansiyeli ortaya konmuştur.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

Bi-LSTM : Bidirectional Long Short-Term Memory (Çift Yönlü Uzun Kısa Vadeli Bellek)
BOA : Bottom of Atmosphere (Atmosferin Altı)
CNN : Convolutional Neural Network (Evrişimli Sinir Ağı)
DL : Deep Learning (Derin Öğrenme)
F1 Score : The harmonic mean of precision and recall (Kesinlik ve hatırlamanın harmonik ortalaması)
GAN : Generative Adversarial Network (Üretken Çekişmeli Ağ)
GIS : Geographic Information System (Coğrafi Bilgi Sistemi)
GRU : Gated Recurrent Unit (Gated Tekrarlayan Birim)
INRA : French National Institute for Agricultural Research (Fransız Ulusal Tarımsal Araştırma Enstitüsü)
Kappa : Cohen's Kappa Coefficient (Cohen'in Kappa Katsayısı)
k-NN : k-Nearest Neighbors (k-En Yakın Komşu)
LiDAR : Light Detection and Ranging (Işık Tespiti ve Mesafe Ölçümü)
LSTM : Long Short-Term Memory (Uzun Kısa Vadeli Bellek)
MAE : Mean Absolute Error (Ortalama Mutlak Hata)
ML : Machine Learning (Makine Öğrenmesi)
MSE : Mean Squared Error (Ortalama Kare Hatası)
NDVI : Normalized Difference Vegetation Index (Normalize Fark Bitki Örtüsü İndeksi)
NLP : Natural Language Processing (Doğal Dil İşleme)
RF : Random Forest (Rastgele Orman)
RGB : Red, Green, Blue (Kırmızı, Yeşil, Mavi (renk kanalları))
RMS : Root Mean Square (Kök Ortalama Kare)
RMSE : Root Mean Squared Error (Kök Ortalama Kare Hatası)
RNN : Recurrent Neural Network (Tekrarlayan Sinir Ağı)
RS : Remote Sensing (Uzaktan Algılama)
SAR : Synthetic Aperture Radar (Sentetik Açıklıklı Radar)
SVM : Support Vector Machine (Destek Vektör Makinesi)
TCNN : Temporal Convolutional Neural Network (Zamansal Evrişimli Sinir Ağı)
TOA : Top of Atmosphere (Atmosferin Üstü)
XGBoost : Extreme Gradient Boosting (Aşırı Gradyan Artırma)

SSLSTM-AE : Semi-Supervised Long Short-Term Memory AutoEncoder (Yarı Denetimli Uzun Kısa Vadeli Bellek Otoenkoder)

ROC : Receiver Operating Characteristic (Alıcı İşletim Karakteristiği)

INTRODUCTION

Remote sensing has become an indispensable tool in modern agriculture, environmental monitoring, and land management. It involves collecting data about the Earth's surface through sensors mounted on satellites or aircraft, which capture various wavelengths of electromagnetic radiation. This technology provides a wealth of information that can be used for various applications, including the classification of crops.

Remote Sensing and Crop Classification

Crop classification is a crucial application of remote sensing, as it allows for the monitoring and management of agricultural resources. By analyzing satellite imagery, it is possible to identify different crop types, monitor crop health, estimate yields, and assess the impact of environmental factors on crop growth. This automated approach significantly reduces the need for labor-intensive field surveys and enhances the accuracy and efficiency of agricultural monitoring.

The use of satellite data, such as that from the Sentinel-2 satellites, has proven particularly effective in crop classification tasks. Sentinel-2 provides high-resolution optical images in 13 spectral bands, ranging from visible to shortwave infrared. These images offer detailed information about the spectral characteristics of crops, which can be used to distinguish between different types. The ability to capture frequent and high-resolution images over large areas makes Sentinel-2 data invaluable for agricultural monitoring.

Challenges and Opportunities

Despite the advantages, several challenges remain in utilizing remote sensing data for crop classification. One significant challenge is the temporal nature of the data, which requires advanced methods to analyze and interpret time series information effectively. Additionally, class imbalances in the dataset, where certain crop types are underrepresented, can lead to biased models and reduced classification accuracy.

Recent advancements in machine learning, particularly deep learning techniques such as Long Short-Term Memory (LSTM) networks and attention mechanisms, offer promising solutions to these challenges. LSTM networks are designed to handle sequential data, making them well-suited for time series analysis. Attention mechanisms, on the other hand, allow models to focus on the most relevant parts of the data, improving feature extraction and overall performance.

Purpose and Contributions

This study aims to enhance crop classification accuracy by developing a hybrid neural network model that combines Bidirectional Long Short-Term Memory (Bi-LSTM) and Temporal Convolutional Neural Networks (TCNN). The proposed method incorporates attention mechanisms to better capture significant features from time series remote sensing data. The primary contributions of this research are:

1. Developing a hybrid neural network model integrating Bi-LSTM and TCNN for improved crop classification.
2. Incorporating attention mechanisms to enhance feature extraction from time series data.
3. Addressing class imbalances in the dataset to improve model accuracy.

The methodology involves using the BreizhCrops dataset, which comprises time series data collected through Sentinel-2 satellite imagery. The dataset is preprocessed to balance class distributions, and the model is trained and evaluated using various performance metrics.

Thesis Outline

This thesis is structured as follows:

Chapter 2: A review of related works on crop classification using satellite time series data.

Chapter 3: The proposed methodology, including the neural network architecture and attention mechanisms.

Chapter 4: Evaluation of the proposed method and comparison with existing approaches.

Chapter 5: Conclusion and recommendations for future research.

In summary, this study seeks to advance the field of crop classification using remote sensing data by leveraging state-of-the-art machine learning techniques. By addressing the challenges associated with temporal data and class imbalances, the proposed approach aims to provide a more accurate and efficient solution for agricultural monitoring.

BASE CONCEPT AND RELATED WORKS

In this chapter, the infrastructure, methods and solutions of various problems that we encountered during this research or that form the basis of the work will be examined. First, we will look at remote sensing and its applications in crop classification. Then the methods based on ttention in the neural network will be selected and how to solve the imbalance of the dataset will be studied. Finally, the related works about crop classification will be studied using time series data.

Remote Sensing and Crop Classification

Remote sensing refers to imaging systems and sensors for collecting data from the Earth's surface at a distance, usually using satellites or aircraft (Lillesand *et al.* 2015). Remote sensing data are used in a variety of applications such as natural resource management, agriculture, and environmental monitoring.

Remote sensing is the acquisition of information related to the Earth's surface that is achieved by sensors mounted on satellites or aircraft. Remote sensing data are useful in a variety of applications such as disaster management, land cover mapping, and environmental monitoring. Remote sensing data can be achieved in different forms, such as thermal, optical, and radar data (Prokop, 2020).

Optical remote sensing data is acquired by sensors that measure the reflected near-infrared and visible light by the Earth's surface. Optical data are useful in identifying various types of land covers, such as forests, urban areas, and crops. Thermal remote sensing data is acquired by sensors that measure the emitted thermal radiation by the Earth's surface. This type of data are used to estimate surface temperature and identify areas of heat loss or gain. Radar remote sensing data is acquired by emitting microwave radiation and measuring the backscattered signal reflected by the Earth's surface. This type of data can penetrate clouds and vegetation, allowing for the identification of surface features that may be obscured by other types of data (Prokop, 2020).

Remote sensing data can be analyzed using various techniques, such as image classification and change detection. Image classification involves grouping pixels in an image into categories based on their spectral characteristics. Change detection involves comparing two or more pictures of an area taken at various times to identify land cover changes or other surface features. These techniques can be used to monitor environmental changes, such as deforestation, urbanization, and land degradation (Prokop, 2020).

Remote sensing is divided into two main types: active and passive. The passive type sensors collect energy which naturally emitted or reflected by the Earth's surface. The active type sensors emit and measure the energy reflected or scattered back from the Earth's surface (Weiss *et al.* 2020).

- Passive Type Remote Sensing: Passive remote sensing sensors include:
  - Imagers: These sensors collect reflected or emitted energy in the near-infrared, thermal infrared, shortwave infrared, and visible wavelengths.
  - Radiometers: These sensors collect emitted energy in the microwave and radio wavelengths.
  - LiDAR: This sensor measures the distance to the Earth's surface using laser pulses.
- Active Type Remote Sensing: Active remote sensing sensors include:
  - Radar: This sensor emits radio waves and then measures the reflected waves.
  - LIDAR: This sensor emits laser pulses to measure the reflected light.

Remote sensing data are useable in different applications, such as (Sishodia *et al.* 2020):

- Monitoring environmental change: Remote sensing data are usable to track changes in vegetation, land cover, water quality, and other environmental indicators.
- Managing natural resources: Remote sensing data are useful to map and monitor natural resources, including forests, fisheries, and mineral deposits.
- Detecting natural disasters: Remote sensing data are used to detect and monitor natural disasters, including wildfires, floods, and earthquakes.

In conclusion, remote sensing is a powerful tool for gathering data related to the Earth's surface. Remote sensing data can be acquired in various forms and analyzed using various techniques to support various applications. Ongoing research is exploring new ways of using remote sensing data in monitoring and managing Earth's environment.

Crop classification is one specific application of remote sensing in agriculture, which involves using remote sensing data to identify and map different types of crops within a given area (Virnodkar *et al.* 2020). Crop health monitoring, yield estimation, and assessment of the impact of environmental factors on crop growth can be used to classify crops.

There are several types of remote sensing data that can be used for crop classification, including optical data, radar data, and multispectral data. Optical data refers to data collected in the near-infrared and visible portions of the electromagnetic spectrum that are used to identify types of crops according to their spectral signatures. Radar data, on the other hand, can penetrate through clouds and vegetation, and can be useful to identify types of crops according to their physical structure. Multispectral data combines both optical and radar data, providing a more comprehensive view of the crop canopy (Gholizadeh & Kopačková, 2019).

For crop classification using remote sensing data, machine learning approaches can be useful in data analysis and identifying patterns related to different crop types. (Virnodkar *et al.* 2020). These algorithms are trained using annotation data, where the crop types within a given area are manually identified and labeled, or using unsupervised learning techniques, where the algorithm identifies patterns in the input data without previous knowledge about the crop types.

Overall, remote sensing and crop classification can be powerful tools for monitoring and managing agricultural systems, that allow obtaining comprehensive information about resources and better decision-making. However, it is important to carefully select and process the appropriate remote sensing data, and to use appropriate machine learning algorithms for the specific application.

Time Series Data

Time series data is a sequence of data points that are indexed or ordered in time (Geiger *et al.* 2020). This type of data is usually used in different fields, such as economics, weather forecasting, finance, and engineering, among others. Analyzing this type of data can identify patterns, trends, and other information related to data that are useful for making predictions or informing decision-making..

Recently, growing interest in using machine learning approaches to analyze time series data (Hewamalage *et al.* 2021). This has caused to development of different algorithms and models, such as decision trees, support vector machines, recurrent neural networks, and others. These models can be used to perform tasks such as forecasting future values, detecting anomalies, and classifying different types of time series data.

One key challenge in working with time series data is dealing with the issue of autocorrelation, which refers to the fact that the values in a time series are often correlated with previous values (Geiger *et al.* 2020). This can make it difficult to extract meaningful relationships and patterns in the input data and may require specialized techniques such as lag analysis or differencing to overcome.

Despite these challenges, time series data remains an important area of research and application, with many potential uses in fields ranging from finance to healthcare (Hewamalage *et al.* 2021). As such, continued development and refinement of techniques to analyze and model time series data is likely to remain an active area of research for years to come.

Satellite data as a time series data is a sequence of measurements taken by a satellite over time (Zeng *et al.* 2020). This type of data can provide valuable information about the Earth's surface changes including land use changes, vegetation, and water resources. Satellite data can be useful in monitoring environmental conditions, tracking climate change impacts, and informing decision-making in various fields, including agriculture, forestry, and natural resource management.

The advantage of satellite time series data is their capability to provide frequent and high-resolution measurements of the land surface over large areas (Viana *et al.* 2019). This makes it possible to track changes in environmental conditions with high accuracy and precision. However, working with satellite time series data can also present challenges, such as dealing with issues related to data quality, cloud cover, and atmospheric interference.

To overcome these challenges, researchers have developed a range of techniques for analyzing and processing satellite time series data. These techniques include methods for filtering out noise and other unwanted signals, as well as algorithms for identifying changes and trends in the data over time (Zeng *et al.* 2020) (Li *et al.* 2020).

Overall, satellite time series data represents a valuable resource for studying and monitoring environmental conditions on Earth. Continued development of techniques for analyzing and processing this data will remain an active area of research in the coming years.

Machine learning and neural network models are valuable tools for analyzing and forecasting based on time series data (Alsumaiei, 2020). Time series data consists of a sequence of data points gathered over time, enabling the observation of system changes and trends over a defined period.

One common approach to analyzing time series data using machine learning is to use autoregressive models, which make predictions based on past values of the time series (Hyndman & Athanasopoulos, 2021). These models can be linear or nonlinear, and that be trained using techniques such as gradient descent or maximum likelihood estimation. Examples of autoregressive models include autoregressive integrated moving average (ARIMA) models and seasonal autoregressive integrated moving average (SARIMA) models.

Neural network models can also be used to analyze time series data, especially when the data is complex and nonlinear (Lyu *et al.* 2019). One of the famous types of neural networks for time series analysis is the recurrent neural network (RNN), which is proper for sequences of data. The RNN includes recurrent connections that able the network to preserve a memory of past input data, making it well-suited for analyzing time series data. Examples of RNN-based models include gated recurrent units (GRUs) and long short-term memory (LSTM) networks (Lyu *et al.* 2019).

Another technique for analyzing time series data using neural networks is to use convolutional neural networks (CNNs), which are typically proper in image analysis but can also be applied to time series data that have a temporal or spatial structure (Van Houdt *et al.* 2020). CNNs can be used to get useful features from the time series data that are relevant to the prediction task and can be trained using supervised learning methods.

Overall, machine learning and neural network models can be powerful tools for analyzing time series data, that make accurate predictions and identify patterns and trends in the input data. However, it is important to carefully select and train the proper model for the specific domain of application, taking into account factors such as complexity and the size of the data, the desired level of accuracy, and available computational resources.

Satellites and Sentinel-2

Sentinel-2 is a constellation of two Earth observation satellites launched by the European Space Agency (ESA) in 2015 and 2017, respectively (Baba *et al.* 2021). The Sentinel-2 satellites are developed to gather high-resolution optical images of the Earth's surface, primarily for land management and environmental monitoring applications. The Sentinel-2 satellites carry a multispectral imager that can capture data in 13 spectral bands, ranging from the visible to the shortwave infrared (Onačillová *et al.* 2022). This allows for comprehensive Earth's surface analysis, including monitoring of vegetation health, land cover changes and land use, and water quality.

One of the key advantages of the Sentinel-2 satellites is their high spatial resolution, which ranges from 10 to 60 meters according to the spectral band (Gubatanga Jr *et al.* 2019). This makes it possible to capture detailed information about small-scale features on the Earth's surface, including individual trees or small bodies of water. The data from the Sentinel-2 satellites is freely available to the public through the Copernicus Open Access Hub, and can be used in a wide range of domains, such as agriculture, forestry, and disaster response (Baba *et al.* 2021). To facilitate the use of Sentinel-2 data, various software tools and platforms have been developed, such as the Sentinel Application Platform (SNAP) and the Google Earth Engine. Overall, Sentinel-2 represents an important resource for monitoring and managing the Earth's natural resources, and will play an effective role in environmental monitoring and research in the coming years. Figure 1 shows the process of image preparation by Sentinel-2 satellite.

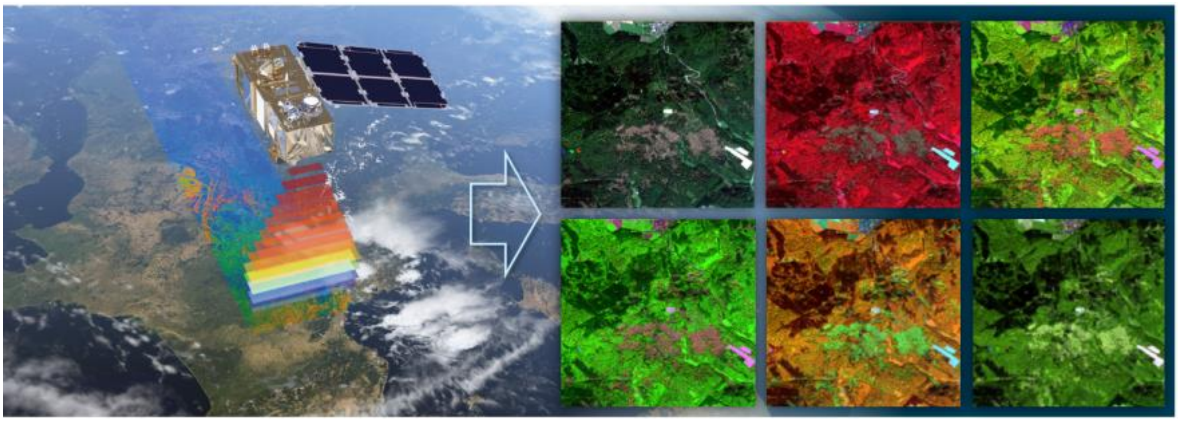

Figure 1. Sentinel-2 satellite working process (Gubatanga Jr *et al.* 2019)

Sentinel-2 is a European Space Agency (ESA) satellite mission designed for Earth observation. In this mission comprises two simmilar satellites were launched that first Sentinel-2A in 2015 and next Sentinel-2B, in 2017. These satellites collects data in 13 spectral bands using a multispectral imaging instrument called the MultiSpectral Instrument (MSI). The Sentinel-2 data has been extensively used for crop classification due to its high spatial resolution and spectral information (Neetu & Ray, 2019) (Xie & Niculescu, 2022). The MSI data is helpful in differentiating between crop types based on their unique spectral characteristics. For instance, the visible region of the spectrum shows different chlorophyll absorption features for different crops, while the near-infrared and shortwave infrared regions reveal different water content and structural characteristics of crops. Several studies have shown the effectiveness of Sentinel-2 data in the classification of crop types (Neetu & Ray, 2019).

Neetu *et al.* (Neetu & Ray, 2019) used Sentinel-2 data to classify five crop types (maize, soybean, cotton, peanut, and sweet potato) in the United States. The authors employed machine learning algorithms to classify the crops based on the spectral information captured by Sentinel-2. They achieved overall accuracies ranging from 83% to 95%, depending on the crop type. Xie *et al.* (Xie & Niculescu, 2022) used Sentinel-2 data to classify three crop types (wheat, barley, and rapeseed) in France. They employed a combination of spectral indices and machine learning algorithms to classify the crops, achieving overall accuracies ranging from 86% to 91%, depending on the crop type.

In conclusion, Sentinel-2 data can provide high-resolution, multispectral data that can be used to distinguish between different crop types. The use of Sentinel-2 data for crop classification is likely to become more widespread in the future, as it can support sustainable agriculture practices (Neetu & Ray, 2019) (Xie & Niculescu, 2022).

Deep Neural Networks

A deep neural network, often referred to as a deep learning model, is a specialized form of artificial neural network. These networks comprise interconnected nodes, or neurons, arranged in multiple layers. They are designed to discern and encode intricate patterns and relationships within input data, employing multiple hidden layers situated between the input and output layers. Deep neural networks have garnered widespread interest and demonstrated notable accomplishments across diverse domains including natural language processing, computer vision, speech recognition, and more. Figure 5 illustrates an example structure of a deep neural network.

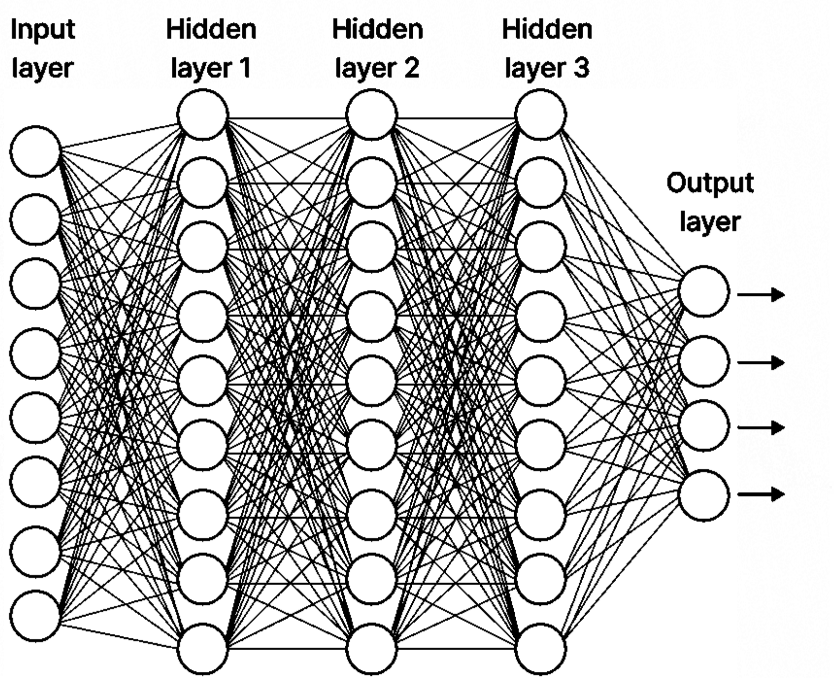

Figure 2. Example of deep neural network structure (Li *et al.* 2021)

With their remarkable focusing power in finding meaning from input data that are ambiguous and complex, these networks can be useful for extracting patterns and identifying complex and difficult techniques for humans and other computer techniques. When the model is trained on input data, it can act like a domain expert for analysis. Neural networks have a very high ability to process complex data and can identify hidden patterns and relationships in the data. By training the network, the network can be used to recognize patterns, interpret data, and predict outcomes. The neural network is able to learn the background information it is given and use it to generate the responses it receives based on the input data. In the following, some important advantages of neural networks have been discussed:

- Adaptive Learning: Adaptive learning is the power of learning and performing tasks according to the knowledge given for preliminary experiences and practice.

- Self-Organization: Self-organization means that an AI network creates an organization for maintaining information that is received during the learning iterations.
- Real-time operation: In the real-time operation of the artificial intelligence network, the network can perform calculations in parallel, and special hardware can be developed and built to take advantage of this capability.
- Fault tolerance without interrupting data encoding: A minor failure of a network results in a corresponding performance degradation, although some network capabilities continue to function even with major damage.

Despite the profits and advantages of neural networks compared to current conventional systems, there are also disadvantages that should be tried to minimize them, such as:

- There are no rules or guidelines in developing a network for a specific application domain.
- In the case of modeling problems, it is not possible to understand the physics of the problem simply by using a neural network. In fact, it is not possible to interact parameters or network structure to process parameters.
- The accuracy of the result is highly dependent on the training size.
- Training the model can be hard or may be impossible.
- It is simply not possible for researchers to predict the generalization of the network.

Generally, there are various effective factors when designing a neural network that should be decided. In between these parameters, we can mention the number of neurons in each layer, the number of layers, the number of training repetitions, and so on. More important than the mentioned, there are factors in terms of training and capacity of the network, which are: the impulse parameter, the learning rate, and the number of hidden neurons.

The number of neurons in the hidden layer

Neurons that are neither in the input layer nor in the output layer are called hidden neurons that are basically hidden. These neurons and their number are black boxes for those interacting with the system. Also, the use of more hidden neurons in layers can increase the performance and processing power of the system. However, more neurons is a condition of more complexity of the training model. The existence of more hidden neurons than needed is similar to a system that has more equations than free variables. Having fewer hidden neurons than required can prevent the system from correctly adapting to the input data and reduce the system's robustness.

Learning rate

The changes that occur in the weights during the training process of the neural network is known as the learning rate. This parameter controls how much the weights change based on the estimated error at each step. Choosing the right learning rate is a challenge because its high value causes the model to quickly learn non-optimal weights and probably not stop at optimal points. On the other hand, the low value of the learning rate may slow down the training process and the neural network may not reach the optimal points completely. Learning rate is usually one of the most important hyperparameters in neural network configuration. Therefore, it is very important to examine its effects on model performance and choose an appropriate value. Methods such as cross-validation and learning rate schedules can help us determine the appropriate learning rate. The effect of the learning rate can be measured by the choice value method for it. Reduced values necessitate more training iterations due to the minor adjustments in weights per update, whereas larger values lead to quicker adjustments and fewer training iterations. However, excessively large values might prompt the model to converge rapidly to a suboptimal solution, while excessively small values might impede progress.

Momentum

Momentum can prevent the system from converging to the saddle point by adding a fraction of the weight of the past update to the current weight and can also help speed up the convergence of the system. When the value of the momentum parameter is high, the previous momentum is added to the current weight, which causes the weights to be updated in the direction where more changes occur. This makes the training process quickly move towards optimization. But an excessively high value of the momentum parameter may cause the system to become unstable. When the momentum value is too large, the previous momentum is added to the current weight, and this can lead to too fast a transition in a direction that ignores more optimal areas. This may cause crossing local optima and getting stuck in unstable regions. As a result, the model will not be able to improve the quality and convergence. Therefore, to use the momentum parameter, you must choose a suitable value.

Number of epochs

The number of repetitions determines when the training stops. This represents the maximum number of iterations when training is performed with minimum error.

Neurons

An artificial neuron in a neural network has its own function. The general function of a neuron consists of calculating the weighted sum of the input parameters and applying this set to an activation function (stimulus function) to produce the output. A neural network usually consists of a collection of neurons organized in layers. These layers are:

- Layer of input neurons: these neurons receive input parameters from outside the network and send their output to other neurons inside the network. Their main task is to receive and introduce input information to the network.
- Layer of intermediate neurons: these neurons receive their input parameters from other neurons in the network and send their output to other neurons in the network. Their main task is information processing.
- Output neurons layer: these neurons receive their input parameters from the neurons in the network and send their output as the final response of the network to the outside of the network. Their main task is to introduce the final response of the network for the processed input vector.

Each layer in the neural network can contain a certain number of neurons, and connections between neurons in different layers are established. With this arrangement, the neural network is able to transfer information from layer to layer and perform different processes in each layer. This hierarchical structure of layers and neurons allows the neural network to process the most complex problems.

Weight

The weight determines the impact of the input on the output of the problem in the network. Considering the fact that different variables input to the network have different values, this evaluation is assigned to them with the help of weights. These weights, which are considered before the output layer and hidden layers, are generated by the method of random numbers and corrected using the network.

Activation functions

Activation functions decide whether a neuron should be activated or not. These functions are integral components of neural networks, where their primary function is to process numerical inputs, which can vary in scale from small to large values within a specified range. The primary goal of these functions is to transform these input values into an output typically constrained within the range of 0 to 1 or within the range of -1 to +1. Activator functions are also called transfer functions. Among the most common ones, we can mention the functions of sigmoid logarithm, sigmoid tangent and linear driving pan. Omitting activation functions within neural networks results in the formation of linear equations governed solely by the weights and bias. While solving linear equations may be straightforward, this approach falls short when tackling intricate problems. In reality, linear equations possess limited capacity for capturing complex data patterns. A neural network devoid of an activation function essentially reduces to a linear regression model. Generally, the integration of activation functions in neural networks plays a pivotal role in enabling them to learn intricate data representations and generate accurate predictions at the output. Figure 6 show different types of activation functions.

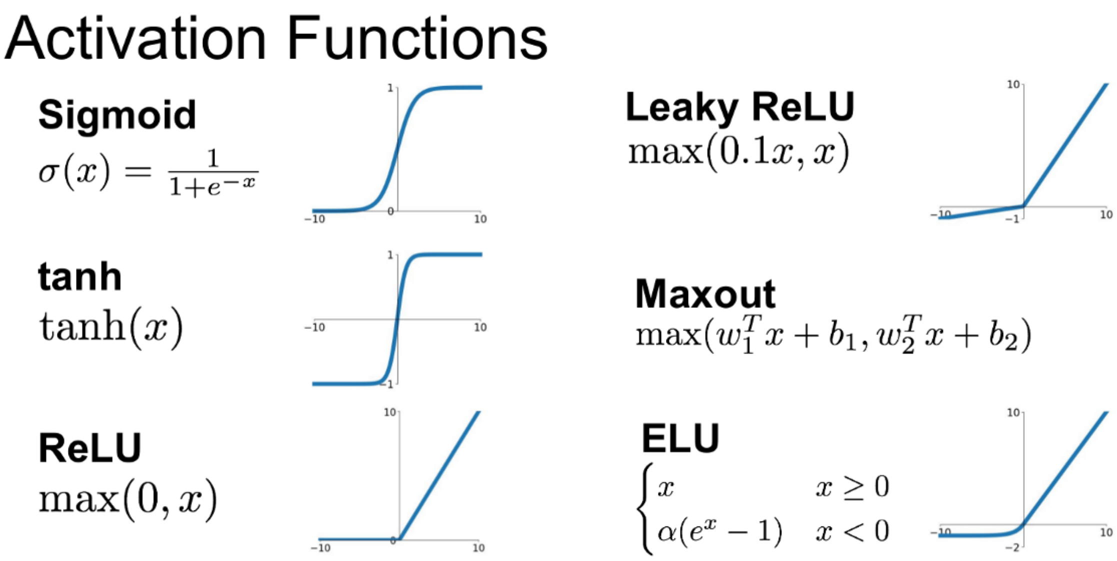

Figure 3. Different type of activation function (Yu *et al.* 2019).

Here are some commonly used types of deep neural networks:

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) find extensive application in image and video analysis tasks. These networks are strategically engineered to adeptly capture spatial hierarchies and local patterns inherent in data. At their core, CNNs employ convolutional layers that employ filters or kernels to process input data. This mechanism empowers the network to autonomously acquire features across varying scales. CNNs have gained recognition for their remarkable capacity to extract meaningful attributes from images, thus enabling tasks such as object recognition, image classification, and image segmentation (Li *et al.* 2021). Figure 7 show the convolution neural network structure.

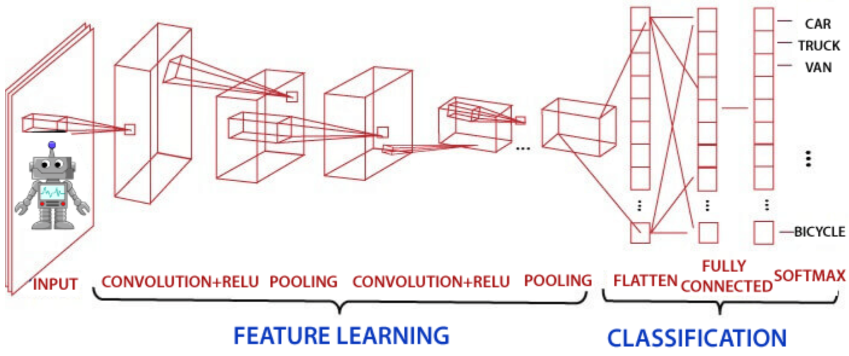

Figure 4. Convolution neural network steps and structure (Li *et al.* 2021).

Recurrent Neural Networks (RNN)

Recurrent Neural Networks (RNNs) are tailored to manage sequential data, prioritizing the sequence of data points. Differing from feedforward networks, RNNs feature connections forming loops, facilitating the retention and transfer of information between consecutive steps. This inherent ability empowers them to preserve memory and apprehend temporal dependencies. RNNs find extensive application across various domains such as speech recognition, natural language processing, and time series analysis (Yu *et al.* 2019). Figure 8 illustrates the structure of a recurrent neural network.

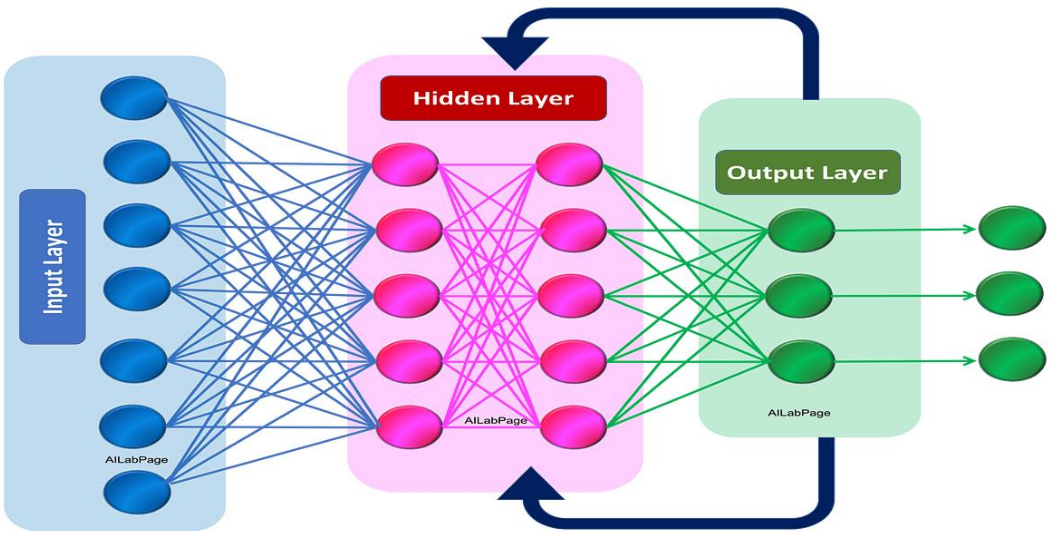

Figure 5. Recurrent neural network steps and structure (Yu *et al.* 2019).

Long Short-Term Memory (LSTM) Networks

LSTM (Long Short-Term Memory) networks represent a specific category of recurrent neural networks designed to mitigate the vanishing gradient problem often encountered in conventional RNNs. LSTMs incorporate extra memory cells and gate mechanisms, which empower them to make selective decisions regarding information retention or forgetting over extended sequences. This unique architecture renders LSTMs highly proficient in managing long-term dependencies within sequential data.

Imbalance Dataset and Solutions

Machine learning algorithms often struggle to process imbalanced datasets, so handling imbalanced datasets is an important challenge. An imbalanced dataset can be handled in several ways as shown in Fig 10, including:

- An undersampling is a method of balancing the distribution of the majority class by reducing the number of instances in it. Small datasets may benefit from this approach, but it may discard potentially useful information and may not be appropriate for all datasets (Junsomboon & Phienthrakul, 2017).
- Oversampling is a technique used to rectify class imbalance by augmenting the number of instances within the minority class, thereby achieving a more equitable distribution between the two classes. For small datasets, this approach can prove effective, but if not practiced carefully, it may result in overfitting (Junsomboon & Phienthrakul, 2017).
- A synthetic sampling technique is used to create new instances in the minority class based on the existing instances. To prevent the generation of unrealistic data, it is necessary to select the sampling method and parameters carefully in order to make this approach feasible for large imbalanced datasets (Ali-Gombe & Elyan, 2019).
- Using a cost-sensitive learning algorithm, the learning algorithm is modified to give more weight to the minority class. A cost matrix must be carefully tuned in order to achieve optimal performance for imbalanced datasets using this approach.
- Methods involving ensembles: An ensemble method involves combining multiple classifiers to improve performance. It is possible to utilize the strengths of multiple algorithms to balance the distribution of classes in imbalanced datasets with the help of this approach.
- Detection of anomalies: Anomaly detection entails the process of recognizing instances that exhibit substantial deviations from the predominant majority class. In datasets in which the minority class consists of rare events or outliers, this approach can be effective.

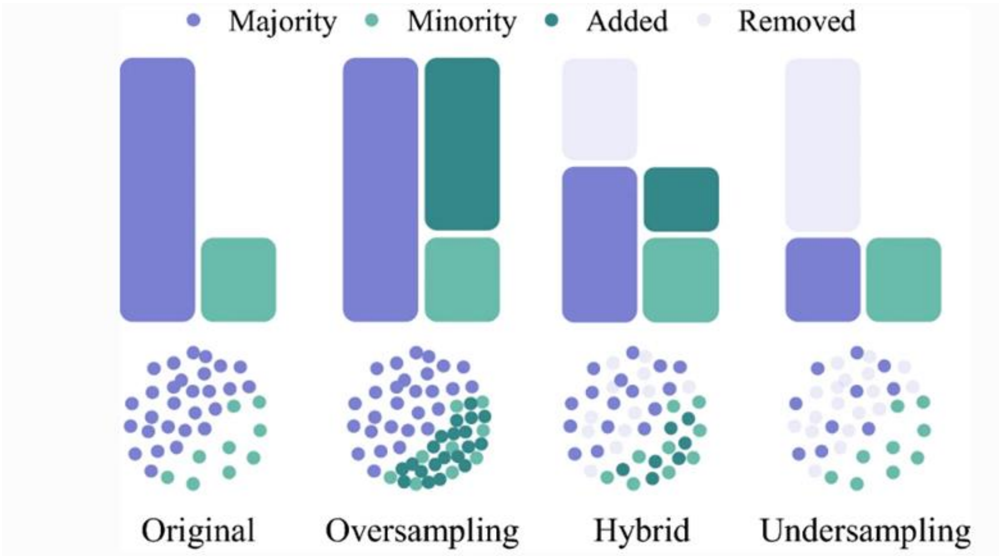

Figure 6. Different methods of handling imbalance dataset (Ali-Gombe & Elyan, 2019)

Additionally, it's crucial to meticulously assess the learning algorithm's performance on a validation set alongside these strategies. Evaluating performance metrics like precision, recall, F1-score, and area under receiver operating characteristic curves (ROCs) offers valuable insights into the algorithm's efficacy, particularly in managing imbalanced datasets. Furthermore, it's essential to factor in the business context and associated costs related to false positives and false negatives when determining an approach to address imbalanced datasets.

LSTM Neural Networks

Long Short-Term Memory (LSTM) is a distinctive architecture within the broader scope of recurrent neural networks (RNNs). Introduced by Hochreiter and Schmidhuber in 1997, LSTMs were crafted to address the limitations encountered by conventional RNNs in retaining and managing long-term dependencies within sequential data. Since their inception, LSTMs have garnered significant acclaim and have been deployed across various fields, encompassing speech recognition, natural language processing, time series analysis, and more.

The fundamental concept underpinning LSTM is the incorporation of memory cells and gate mechanisms, which grant the network the ability to make deliberate decisions regarding information retention or deletion over extended sequences. This enables LSTMs to effectively capture and propagate relevant information while mitigating the vanishing gradient problem, which can occur in traditional RNNs.

The architecture of an LSTM network consists of repeating LSTM blocks, each containing multiple interconnected memory cells. he memory cells within LSTM networks play a pivotal role in the storage and dynamic updating of information throughout the sequence. These memory cells consist of three critical components: an input gate, a forget gate, and an output gate. These gate mechanisms effectively govern the ingress, egress, and internal flow of information within each memory cell. The LSTM network operates in a sequential manner, processing one input element at a time (Smagulova & James, 2019). The process within an LSTM block can be summarized as follows:

1. **Input Processing:** The LSTM network takes an input element and subjects it to processing through an activation function, commonly employing functions like the rectified linear unit (ReLU) or hyperbolic tangent (tanh).
2. **Gating Mechanisms:** The input gate is responsible for making decisions about which aspects of incoming information should be preserved within the memory cell. It employs a sigmoid function to produce values ranging from 0 to 1, signifying the relative significance of various input elements.
3. **Memory Cell Update:** The forget gate is tasked with determining what information should be omitted from the memory cell. It utilizes a sigmoid function to assess the extent to which the prior memory cell state should be erased. The integration of new information with the current memory cell state is facilitated by the input gate, enabling the memory cell to refresh its contents.
4. **Output Generation:** The output gate plays a pivotal role in regulating the quantity of information to be extracted from the memory cell. It employs a sigmoid function to make determinations regarding which segments of the updated memory cell state should be employed in generating the output.

The information flow within an LSTM network empowers it to capture and maintain long-term dependencies. The memory cells possess the capability to preserve information across extended sequences, while the gate mechanisms provide the network with the ability to make selective decisions regarding information retention or dismissal based on its contextual relevance. Consequently, LSTMs have demonstrated exceptional effectiveness across a diverse array of applications:

- **Natural Language Processing:** LSTMs are widely used for tasks such as machine translation , language modeling, sentiment analysis, and text generation.
- **Speech Recognition:** LSTMs have been successful in automatic speech recognition systems, where they can effectively model speech sequences and capture phonetic dependencies.
- **Time Series Analysis:** LSTMs excel in forecasting and analyzing time series data, enabling accurate predictions and anomaly detection.

- **Image Captioning:** LSTMs can be combined with convolutional neural networks (CNNs) to generate descriptive captions for images.
- **Handwriting Recognition:** LSTMs have been applied to recognize and interpret handwritten text, enabling the development of handwriting recognition systems.

LSTMs have been further extended and enhanced with variations such as Gated Recurrent Units (GRU), which have a simplified architecture but retain similar capabilities. Additionally, techniques like bidirectional LSTMs, which process sequences in both forward and backward directions, have been developed to capture dependencies from both past and future contexts. Overall, LSTMs have revolutionized the field of sequential data analysis, allowing neural networks to handle long-term dependencies and achieve state-of-the-art performance in various tasks that involve sequential data (Bashar, 2019).

Temporal Convolution Neural Network

Temporal Convolutional Neural Networks (TCN) are a type of deep learning architecture specifically designed for processing sequential data, such as time series or sequential audio signals. TCNs leverage the power of convolutional neural networks (CNNs) to capture temporal dependencies and extract meaningful features from the input data (Bui *et al.* 2022).

Unlike traditional CNNs, which primarily focus on spatial relationships in images, TCNs operate on sequential data by using 1D convolutions. These convolutions analyze local patterns and relationships between adjacent elements within the sequence, allowing the TCN to capture both short-term and long-term dependencies. The key characteristics and components of TCNs are as follows:

1. **Temporal Convolutional Layers:** TCNs consist of multiple layers of 1D convolutional filters. These filters traverse the input sequence, scanning and capturing localized features at every position. The filters have a receptive field that determines the number of past elements the filter considers. By stacking multiple convolutional layers, TCNs can capture increasingly complex temporal patterns.
2. **Dilated Convolutions:** TCNs often employ dilated convolutions, also known as atrous convolutions, to increase the receptive field without significantly increasing the number of parameters. Dilated convolutions introduce gaps between filter elements, allowing them to capture information from a broader context. This enables TCNs to capture long-term dependencies efficiently.

3. **Residual Connections:** To address the vanishing gradient problem and improve gradient flow, TCNs can incorporate residual connections. Residual connections allow the network to learn residual representations by directly connecting the input of a convolutional layer to its output. This helps in preserving important information and facilitates training of deeper TCN architectures.
4. **Pooling and Downsampling:** TCNs can utilize pooling or downsampling operations to reduce the dimensionality of the feature maps and capture higher-level abstractions. Pooling operations such as max pooling or average pooling can be applied to extract the most salient features from the local regions.
5. **Fully Connected Layers:** Following the convolutional layers, TCNs often include fully connected layers to aggregate the extracted features and make final predictions. These layers can incorporate additional non-linearities and learn complex relationships between the extracted features and the target output.

TCNs have demonstrated excellent performance in various applications involving sequential data (Pandey & Wang, 2019):

- **Time Series Forecasting:** TCNs can effectively model and forecast time series data by capturing temporal patterns and dependencies.
- **Speech Recognition:** TCNs have been successfully applied to speech recognition tasks, where they can learn representations from sequential audio signals and perform phoneme or word recognition.
- **Natural Language Processing:** TCNs have shown promising results in various tasks like sentiment analysis, language modeling, and text classification where they can process sequential data in the form of text.
- **Action Recognition:** TCNs can analyze sequential video data to recognize and classify human actions, enabling applications in video surveillance, sports analysis, and human-computer interaction.
- **Anomaly Detection:** TCNs can identify anomalies or outliers in time series data by learning the normal patterns and detecting deviations from them.

TCNs offer several advantages, including parallel processing of sequential data, capturing long-term dependencies efficiently, and exhibiting translation equivariance properties. They have proven to be effective alternatives to traditional recurrent neural networks (RNNs) in certain applications, especially when the temporal relationships in the data are crucial but require more efficient processing.

With their ability to model sequential data and extract meaningful features, TCNs have become a valuable tool for analyzing and understanding various types of sequential data, facilitating advancements in fields such as speech recognition, signal processing, and natural language understanding.

Attention Based Neural Networks

Attention-based neural networks are a type of artificial neural network that incorporates the concept of attention from cognitive psychology. The attention mechanism empowers the network to concentrate its computational resources on particular segments of the input data that bear the utmost relevance to the current task, effectively filtering out irrelevant information. Extensive evidence demonstrates that this mechanism enhances the performance of neural networks across a spectrum of natural language processing tasks, including machine translation and text summarization (Garg *et al.* 2019).

Within an attention-based neural network, the input data undergoes processing through an encoder, resulting in the creation of a sequence of hidden representations. Subsequently, the attention mechanism calculates a series of weights that signify the significance of each hidden representation in relation to the given task. These weights are employed to calculate a weighted summation of the hidden representations, which is subsequently fed into a decoder to produce the desired output (Garg *et al.* 2019).

One of the key advantages of attention-based neural networks is their ability to handle variable-length input data, which is common in natural language processing tasks. The attention mechanism grants the network the ability to discern and focus on segments of the input that are of utmost relevance to the task, regardless of their positions within the input sequence (Zhu *et al.* 2019).

In conclusion, attention-based neural networks are a powerful tool for natural language processing tasks, as they allow the network to selectively attend to relevant parts of the input data. The incorporation of attention mechanisms has led to significant improvements in the performance of neural networks on various tasks (Zhu *et al.* 2019).

In addition to natural language processing tasks, attention-based neural networks have been applied to other domains, such as computer vision and speech recognition. For example, in computer vision, attention mechanisms have been used to selectively attend to different regions of an image for tasks such as image captioning and object detection (Ding *et al.* 2019) (Standvoss *et al.* 2020). In speech recognition, attention mechanisms have been used to align acoustic features with corresponding phoneme sequences, improving the accuracy of speech recognition systems.

One of the challenges of attention-based neural networks is their computational complexity, especially for long input sequences. Several techniques have been proposed to address this issue, such as using a fixed-size window of input data for attention computation (Cheng & Cheng, 2019) or using a hierarchical attention mechanism that attends to different levels of the input data (Han *et al.* 2023).

Another area of research for attention-based neural networks is the exploration of different types of attention mechanisms, such as self-attention and multi-head attention (Wang *et al.* 2020). Self-attention empowers the network to simultaneously consider various sections of the input sequence, whereas multi-head attention enables the network to examine different segments of the input by employing multiple attention mechanisms.

In conclusion, attention-based neural networks are a powerful tool for various machine learning tasks, allowing the network to selectively attend to relevant parts of the input data. While there are computational challenges associated with attention-based neural networks, ongoing research is exploring ways to address these challenges and improve the performance of these networks.

Crop Classification

Crop classification refers to the process of categorizing or classifying different types of crops or vegetation in agricultural or remote sensing applications. It involves using various techniques, such as image analysis, machine learning, and data mining, to identify and differentiate between different crop classes or categories.

Crop classification plays a crucial role in several domains, including precision agriculture, land management, environmental monitoring, and food security. By accurately classifying crops, researchers, farmers, and policymakers can gain valuable insights into agricultural practices, crop health, yield estimation, and resource allocation (Murmu & Biswas, 2015).

There are different approaches to crop classification, depending on the available data and the desired level of accuracy. Some commonly used techniques include:

- **Remote Sensing and Satellite Imagery:** Remote sensing data, such as multispectral or hyperspectral satellite imagery, can provide valuable information about crop characteristics. By analyzing the spectral signatures of crops, researchers can classify different crop types based on their unique reflectance patterns in different wavelengths.

- **Machine Learning and Data Mining:** Machine learning algorithms, such as random forests, decision trees, support vector machines (SVM), and deep learning models, can be trained on labeled crop data to automatically classify crops based on input features. These features may include spectral information, vegetation indices, textural properties, or other relevant attributes.
- **Crop Phenology and Growth Patterns:** Crop classification can also be based on temporal patterns and phenological characteristics. By analyzing the growth stages, flowering patterns, or seasonal changes in crops, it is possible to differentiate between different types of crops.
- **Ground Surveys and Field Observations:** Ground surveys, field visits, and data collected through ground-based sensors or drones can provide valuable ground truth information for crop classification. This data can be used to validate and refine classification models and improve accuracy.

The accuracy of crop classification depends on various factors, including the quality and resolution of the data, the choice of classification algorithm, the availability of training data, and the expertise of the analysts. Continuous advancements in remote sensing technology, machine learning techniques, and data collection methods have contributed to significant improvements in crop classification accuracy in recent years.

Crop classification has several important applications in the field of agriculture and beyond. Some of the key applications include (Virnodkar *et al.* 2020):

1. **Precision Agriculture:** Crop classification helps in precision agriculture by providing information about the spatial distribution of different crop types within a field. This information can be used to optimize resource allocation, such as adjusting irrigation, fertilization, and pesticide application based on the specific needs of different crops.
2. **Crop Monitoring and Management:** By classifying crops, farmers and agronomists can monitor the health, growth, and development of different crop types over time. This information can assist in identifying potential issues like disease outbreaks, nutrient deficiencies, or pest infestations, allowing for timely intervention and targeted management strategies.
3. **Yield Estimation:** Accurate crop classification enables estimation of crop yield at various scales, from individual fields to regional or national levels. By knowing the

distribution and types of crops, researchers and policymakers can make informed decisions regarding food security, market planning, and resource management.

4. **Land Use Planning:** Crop classification helps in understanding the spatial distribution of different crops across a landscape, which is vital for land use planning. It assists in assessing the suitability of different areas for specific crops, identifying potential areas for expansion or intensification, and supporting sustainable land management practices.
5. **Environmental Monitoring:** Crop classification provides valuable information for environmental monitoring and conservation efforts. It helps in studying the impact of agricultural practices on ecosystems, assessing biodiversity, monitoring changes in land cover, and identifying areas at risk of degradation or deforestation.
6. **Insurance and Risk Assessment:** The categorization of crops serves a purpose in agricultural insurance and the evaluation of risks. By accurately classifying crops, insurers can assess the risks associated with specific crop types and regions, determine insurance premiums, and Offering financial safeguards to farmers in case of crop losses resulting from natural disasters or unforeseen circumstances.
7. **Climate Change Studies:** Crop classification contributes to climate change studies by analyzing the distribution and changes in crop types over time. It helps in understanding the impact of climate change on agricultural systems, identifying vulnerability hotspots, and developing adaptation strategies.

These applications highlight the significance of crop classification in improving agricultural practices, optimizing resource allocation, ensuring food security, and supporting sustainable land management. By accurately identifying and monitoring crop types, stakeholders can make informed decisions to enhance productivity, reduce environmental impacts, and promote sustainable agricultural practices. Overall, crop classification is a valuable tool for understanding agricultural landscapes, monitoring crop health, optimizing farming practices, and making informed decisions related to crop management and land use.

BreizhCrop Dataset

BreizhCrops is a dataset featuring time series of satellite images tailored for crop type classification. This dataset incorporates aggregated label information alongside Sentinel-2 top-of-atmosphere and bottom-of-atmosphere time series data, spanning the geographical expanse of Brittany (referred to as 'Breizh' in the local dialect), situated in northwestern France. Curated by Marc Rußwurm, Charlotte Pelletier, Maximilian Zollner, Sébastien Lefèvre, and Marco Körner, the dataset was unveiled in 2020 (Rußwurm et al., 2020).

The BreizhCrops dataset contains about 610,000 labeled observations per processing level. Each observation corresponds to a multivariate time series obtained by averaging reflectance values extracted from Sentinel-2 images at the crop field level. The dataset covers nine crop types: barley, wheat, rapeseed, corn, sunflower, orchards, nuts, permanent meadows, and temporary meadows. The field labels have been gathered in the year 2017.

The BreizhCrops dataset serves as a valuable asset for both researchers and professionals engaged in crop type classification using satellite imagery. The dataset is large and diverse, and it covers a variety of crop types. The dataset is also well-documented and organized, making it easy to use.

Here are some of the key features of the BreizhCrops dataset:

- **Large and diverse**: The dataset contains about 610,000 labeled observations per processing level, covering nine crop types.
- **Well-documented and organized**: The dataset is well-documented and organized, making it easy to use. The documentation includes information on the data format, the labels, and the evaluation metrics.
- **Freely available:** The BreizhCrops dataset is freely available for research and educational purposes.

The Sentinel-2 images in the dataset are in top-of-atmosphere (TOA) and bottom-of-atmosphere (BOA) reflectance. This allows users to experiment with different ways of processing the data, such as atmospheric correction (Rußwurm et al., 2020).

The labels for the crop fields are from the French National Institute of Geographic and Forest Information (IGN). The labels are based on field surveys and are accurate to the field level. The BreizhCrops dataset is split into three partitions: training, validation, and test. This allows users to train and evaluate their models on different subsets of the data.

The BreizhCrops dataset is accompanied by a paper that provides more details about the dataset and the evaluation results. The paper also discusses the challenges of crop type classification from satellite imagery and the potential applications of the BreizhCrops dataset.

Related Works

ime series analysis proves invaluable in discerning alterations in land cover over time, encompassing phenomena like deforestation, urban sprawl, or shifts in agricultural land use. This data is pivotal for comprehending the catalysts behind land use transformation and its ecological ramifications (Yan *et al.* 2019). The scrutiny of time series data emerges as a potent tool in appraising the efficacy of land management initiatives, including conservation endeavors or land rehabilitation endeavors (MohanRajan *et al.* 2020). By tracking fluctuations in land cover over time, it becomes feasible to pinpoint regions benefiting from positive management interventions and areas necessitating further enhancement.

Utilizing time series analysis can bolster land use planning efforts by furnishing insights into trends pertaining to land use and land cover, facilitating informed decision-making processes. This data aids in discerning areas warranting encouragement or restriction for development, factoring in environmental, social, and economic considerations. Ultimately, time series land cover classification stands as a pivotal tool for comprehending and regulating land use transitions, evaluating the efficacy of land management strategies, guiding land use planning decisions, and scrutinizing the repercussions of climate change on ecosystems (Toh *et al.* 2018).

Classification of satellite image time series stands as a fundamental challenge with strong relevance to numerous land-related applications, including tasks like land cover mapping and change detection (Yuan *et al.* 2019), as well as the identification of specific vegetation species (Immitzer *et al.* 2016). Devadas *et al.* (Devadas *et al.* 2012) introduced a technique for analyzing multi-temporal remote sensing images, aimed at detecting shifts in crop types across summer and winter seasons. The assessment of SVM model accuracy in classification heavily relies on vegetation index time series. Deep Learning (DL) has already been harnessed by researchers to tackle diverse challenges within remote sensing. In addressing the issue of unknown classes impacting hyperspectral imagery classification outcomes in open-world scenarios, Liu *et al.* (Liu *et al.* 2020) devised a multitask approach involving classification and reconstruction using DL.

Baroud *et al.* (Baroud *et al.* 2021) introduced a pioneering time series classification framework founded on multi-task learning with graph convolutional networks, aiming at enhancing land use and land cover classification. Demonstrated through experimentation across various remote sensing datasets, this framework exhibited heightened accuracy compared to conventional methodologies. Liu *et al.* (Liu *et al.* 2020) proposed an approach for spatiotemporal classification of remote sensing imagery employing recurrent neural networks. Meanwhile, Lee *et al.* (Lee *et al.* 2018) employed Landsat spectral indices time series to classify land cover, employing spectral indices from time series data for this classification task. In their publication, Masolele *et al.* (Masolele *et al.* 2022) introduced a deep learning-driven methodology for crop type classification, leveraging Sentinel-2 time series data. The method was validated using an Ethiopian dataset, exhibiting superior accuracy compared to conventional techniques. These studies underscore the efficacy of time series approaches in land use and land cover classification, demonstrating the potential of deep learning and other advanced methodologies in enhancing classification accuracy.

In 2019, a study introduced a spatiotemporal fusion technique for mapping land use and land cover, utilizing an enhanced random forest algorithm that integrates both Landsat and MODIS data (Li *et al.* 2021). Validation tests conducted on a dataset from China demonstrated the method's high accuracy.

Furthermore, in (Mazzia *et al.* 2019), an optimal deep learning model for pixel-based Land Cover and Land Use Change (LC&CC) analysis was presented. This model leveraged multi-temporal Sentinel-2 imagery and focused on the central north region of Italy. Performance evaluation involved a comparison with various machine learning algorithms, including support vector machines (SVMs), random forests (RFs), kernel SVMs, and gradient boosting machines (XGBoosts). The findings indicate that the proposed approach surpassed the performance of the aforementioned methods.

Navnath *et al.* (Navnath *et al.* 2022) deployed various models, such as bidirectional gated recurrent units (GRUs), temporal convolutional neural networks (TCNNs), combinations of GRUs with TCNNs, TCNNs with GRUs, and hybrid architectures merging GRUs and TCNNs. The objective of this study is to introduce an integrated framework for land cover classification on Reunion Island, leveraging univariate, multivariate, and pixel coordinates. Integration of univariate and multivariate data with recurrent neural networks resulted in enhanced performance of class labels, reflected in higher F1 scores across all class labels. Table 1 show the related works about crop classification.

Tablo 1. Related Works about Crop Classification

Method	**Description**	**Ref.**
Identifying vegetation species	Mapping and detecting changes in land cover	(MohanRajan *et al.* 2020)
Spatiotemporal classification	Spatiotemporal classification of remote sensing imagery	(Devadas *et al.* 2012)
Landsat spectral indices to classify land cover	Spectral classify	(Baroud *et al.* 2021)
Spatiotemporal fusion approach	land use and land cover mapping	(Lee *et al.* 2018)
LC&CC	Optimal deep learning model for pixel-based	(Mazzia *et al.* 2019)
TCNNs used for crop classification	GRUs combined with TCNNs to classify crops	(Navnath *et al.* 2022)

Overview of Datasets Used for Crop Classification

In recent years, advancements in satellite technology and machine learning methods have facilitated the development of numerous datasets for crop classification. These datasets provide valuable resources for remote sensing experts and agricultural researchers to develop and test various classification models. The datasets vary in terms of region, time period, satellite sources, and the number of classes they cover. They offer unique features and resolutions, allowing for detailed analyses of different crop types and land cover categories. Below is an overview of some of the most widely used datasets in the field, highlighting their key characteristics and applications.

Tablo 2. Overview of Datasets Used for Crop Classification

Dataset Name	Region	Year	Satellite Source	Classes
Time Series Land Cover Classification Challenge (TiSeLaC) (TiSeLaC, (2014	Reunion Island	2014	Landsat 8 OLI	land cover 9 classes
BreizhCrops (BreizhCrops, 2017-2018)	Brittany, France	2018-2017	Sentinel-2	crop classes 9
Dynamic Earth NET (DENETHOR) ((DENETHOR, 2018-2019	Northern Germany	2019-2018	Sentinel-1, Sentinel-2, Planet Fusion	classes 9
TimeSen2Crop (TimeSen2Crop, 2017-(2019	Austria	2019-2017	Sentinel-2	16 crop types
Panoptic Agricultural Satellite TIme Series (PASTIS) (PASTIS, 2018-(2019	France	2019-2018	Sentinel-1, Sentinel-2	crop types 18 + background
EuroCrops(EuroCrops, (2018-2021	European Union	2021-2018	Various	to 320 14 classes
RapidAI4EO(RapidAI4EO, (2020	Europe	2020	Planet, Sentinel-2	Multi-class labels based on CORINE Land Cover
Sen4AgriNet(Sen4AgriNet, (multiple years	Multiple Regions	Multiple Years	Sentinel-2	Various

These datasets have been pivotal in enhancing our understanding of crop patterns and land use changes. They support a wide range of applications, from local to global scales, and are integral for developing automated solutions for crop monitoring, yield prediction, and sustainable agricultural practices. The availability of high-resolution, multi-temporal data has significantly contributed to the accuracy and efficiency of crop classification models.

Conclusion

In this chapter, the study focused on the foundational sciences relevant to the research. Initially, the science of remote sensing and satellite technologies was explored. This was followed by an examination of time series data, machine learning methods, and classification techniques. Next, various types of neural networks were discussed. Finally, a comprehensive review of the relevant literature was provided. Additionally, the dataset I used in this study was presented, along with a comparison of other datasets and their differences.

PROPOSED METHOD

The proposed method (Bandar & Coşkunçay, 2024) is described in full in this chapter. In the following, the presented methodology will be explained and the designed neural network will be explained with its components. In the following, the imbalance of the data set will be checked and the method of solving this problem will be presented. In general, we will examine the basic challenges that we face in the design of neural network and time series data and provide their solutions.

Proposed Method

A time series dataset is used to classify crops in this research. In order to properly train time series data, models with high learning power should be used in sequences. In this regard, the neural network based on LSTM will be used. To strengthen the efficiency of this network, we need a parallel network with an attention-based approach. The necessity of this network arises from the large areas of satellite images that change over time in certain parts. Focusing on these specific areas allows us to access parts of the data that significantly impact learning, enabling the model to recognize crop types. Additionally, another parallel layer processes the image from a more general point of view, making it easier to categorize each crop.

Recent studies have identified two primary challenges in analyzing remote sensing time series data. Firstly, extracting significant features using attention mechanisms has shown promise in enhancing classification accuracy. For instance, extracting significant features using attention mechanisms has shown promise in enhancing classification accuracy (Zhao & Li, 2019). Similarly, attention-based LSTM networks outperformed traditional machine learning methods in identifying large-scale winter wheat, thus confirming the potential of attention mechanisms in handling complex agricultural datasets (Guan et al., 2019).

Furthermore, the combination of Convolutional Neural Networks (CNN) with LSTM networks has proven effective in handling both spatial and temporal features of remote sensing data. For example, combining CNN and LSTM models enhances the classification performance by effectively capturing spatial-temporal features in satellite images (Rußwurm & Körner, 2018). Additionally, integrating CNN with LSTM and attention mechanisms significantly improved the accuracy of crop classification tasks (Wang et al., 2018).

Secondly, the imbalance between classes within the collected data poses a challenge to the learning model's performance. This issue is particularly pronounced due to the nature of agricultural product data and the limited cultivation of certain crops. Addressing these imbalances by proposing data preprocessing and augmentation techniques enhances model performance in crop type identification and spatial mapping using Sentinel-2 satellite data (Gumma et al., 2020). These insights guided our decision to adopt a method combining CNN, LSTM, and attention mechanisms to effectively manage the complexities of remote sensing time series data and improve classification accuracy. In the forthcoming sections, we will delve into methods for addressing these imbalances and the mechanism of attention.

Methodology

As depicted in Figure 11, a sequence of data preparation steps was undertaken to transform the input data into a format compatible with the neural network. Prior to employing the neural network, a series of data preparation procedures were executed to enhance accuracy. These processes involved several steps aimed at normalizing the existing data. Data normalization is a common preprocessing technique employed to enhance the performance and convergence of neural networks. It involves scaling the input dataset to have a mean of zero and a standard deviation of one, or scaling it to a specific range, such as [0, 1] or [-1, 1]. The benefits of data normalization in neural networks include:

- Improved convergence: Normalization promotes stable and swift convergence of neural networks. Unnormalized input data may lead to uneven network weights, causing slow convergence or divergence. Normalization ensures inputs are on a uniform scale, thus averting such issues.
- Reduction of overfitting: Normalization aids in mitigating overfitting, where a neural network excessively tailors itself to the training data, resulting in suboptimal performance on new, unseen data. By minimizing the influence of outliers, normalization renders the model less sensitive to input variations.
- Enhanced generalization: Normalization also fosters improved generalization in neural networks. By diminishing the impact of outliers and ensuring uniform input scales, normalization enables the network to learn more robust and transferable features applicable to a broader range of inputs.

In the subsequent phase of the process, class balancing will be implemented. This balancing act is crucial to prevent network bias toward any specific class, while also ensuring that the network possesses equal efficacy in detecting all classes.

It's time to prepare the data for classification, marking the subsequent stage of data processing. Given that the study's data comprises time series, it's imperative to categorize these data into temporal categories to integrate them into our network. Consequently, data reformatting is necessary to align with this objective. Following data preparation, it is segregated into two distinct categories - training and testing. The training data serves as input for the neural network, while the test data evaluates the effectiveness of the extracted neural network model. Among the neural networks utilized, attention-based and convolutional neural networks are featured prominently.

There exist two distinct types of convolutional neural networks: temporal convolutional neural networks, which capture features from the entire time series dataset, and attentional convolutional neural networks, which focus on extracting the most salient segments of sequential data. Following the amalgamation of these two sets of features, the fully connected layer of the model utilizes a fully connected network to map these features to labels in the final model. Subsequently, after the neural network has undergone comprehensive training, we employ various evaluation metrics. Some of these metrics include precision, recall, F-1 score, and kappa score, which serve as benchmarks for assessing the neural network's performance.

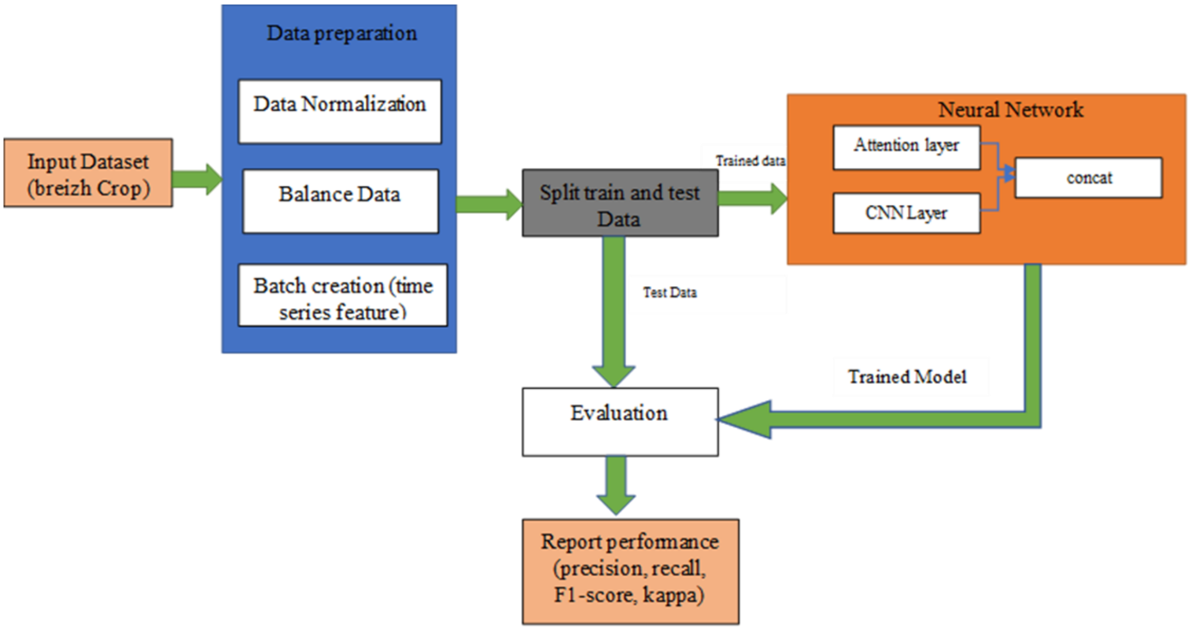

Figure 7. The steps of the model training and evaluation methodology (Bandar & Coşkunçay, 2024)

Attention Mechanism

In recent years, attention-based deep learning models have surged in popularity. Particularly in tasks like machine translation, where input and output sequences vary in length and specific segments of the input sequence hold more significance in generating particular parts of the output sequence, these methods prove invaluable (Junsomboon & Phienthrakul, 2017). Unlike typical neural networks that treat all inputs uniformly, attention-based neural networks selectively focus on certain inputs while disregarding others (Ali-Gombe & Elyan, 2019). This selective focus is achieved through a soft or "learned" alignment, aligning input and output sequences. Within attention-based neural networks, output elements are generated using a distinct "attention mechanism" that learns to assign weights to different segments of the input sequence based on their importance. Essentially, attention mechanisms streamline input sequence processing by assigning weights, enabling the computation of a weighted sum of these inputs.

Following this, the calculated weighted sum assumes a pivotal role in shaping the network's output (Werner de Vargas *et al.* 2023). Attention mechanisms are classified in various ways, with "soft" or "content-based" attention being a prevalent categorization. In this approach, attention weights are determined by measuring the similarity between the current decoder state and each input element. Inputs with greater similarity receive higher weights. Research has demonstrated the effectiveness of attention-based neural networks across a diverse array of time series tasks (Mei *et al.* 2019).

Time series tasks such as forecasting, anomaly detection, and classification have been shown to benefit significantly from attention mechanisms. In these tasks, attention mechanisms can be applied to time series data by treating a sequence of time steps as the input sequence and focusing on the most relevant time steps during each step of the decoding process. This method is analogous to approaches used in natural language processing, where the model attends to different parts of the input sequence throughout the decoding process.

In time series forecasting, for instance, the model is trained to predict a series' value at a future time step. The attention mechanism helps identify the most pertinent past time steps to consider during each step of the prediction process. Additionally, self-attention mechanisms can capture temporal dependencies within time series data, effectively handling long-term dependencies by allowing the model to attend to different parts of the time series at various levels of abstraction.

Solution for imbalanced class labels problem

In numerous agricultural regions, the cultivation landscape is primarily characterized by a handful of crops like corn, meadows, and wheat, which are extensively grown. Nevertheless, local authorities also require accurate classification of other vegetation types to a reasonable degree (Rußwurm & Korner, 2017). Due to the limited agricultural land available for certain crops, the dataset is unbalanced. Additionally, some crops are grown on extensive agricultural land due to high demand. To address this imbalance, this study employs an undersampling approach to reduce the number of instances in categories with a large number of classes. Undersampling techniques encompass the process of decreasing the number of instances within the majority class, which is the class with a greater number of instances, in order to bring it into closer alignment with the minority class, which consists of fewer instances (Junsomboon & Phienthrakul, 2017). The undersampling method mechanism is illustrated in Figure 12. To balance the dataset, classes with a small number of instances are removed. Given the time series nature of the data, generating artificial data or employing oversampling techniques is unsuitable, as these approaches have proven ineffective and can diminish the neural network's efficiency. Therefore, to maintain the neural network's accuracy, this research excludes classes with a small number of instances, removing them from the dataset.

Figure 8. Undersampling from the majority class in the dataset (Bandar & Coşkunçay, 2024)

Neural Network Architecture

A parallel neural network architecture is proposed, comprising two distinct architectures. The first involves a BI-LSTM layer integrated with an attention mechanism, allowing for the extraction of significant features from time series data. This structure includes a dropout layer followed by another LSTM layer, which sorts and flattens these features. The extracted features are then sequentially and one-dimensionally fed into the concatenate layer. Simultaneously, a Temporal-CNN layer processes the same batch of input data in parallel. This design enables the extraction of general characteristics of the time series data, providing a comprehensive understanding of the data's sequence in conjunction with the attention layer's characteristics. The flattened, one-dimensional output from this layer is also passed to the concatenate layer. Features from both neural networks are then mapped to the Softmax activation function for each time series dataset. Figure 13 illustrates the overall structure of this architecture.

The BI-LSTM architecture offers an advantage over a simple LSTM by capturing the effective features of the time series from both directions, rather than just one. This bidirectional approach ensures a more comprehensive extraction of features. Additionally, the Temporal-CNN neural network contributes by transferring the broader characteristics of the time series to the next layer, providing a more general perspective. Consequently, this architecture allows for the simultaneous extraction of both local and general features from the time series data. These features enable mapping to the labels from both perspectives. In summary, the proposed method's superiority is characterized by: (a) navigating effective local features bidirectionally, (b) extracting general features, and (c) simultaneously utilizing both types of features to identify the label.

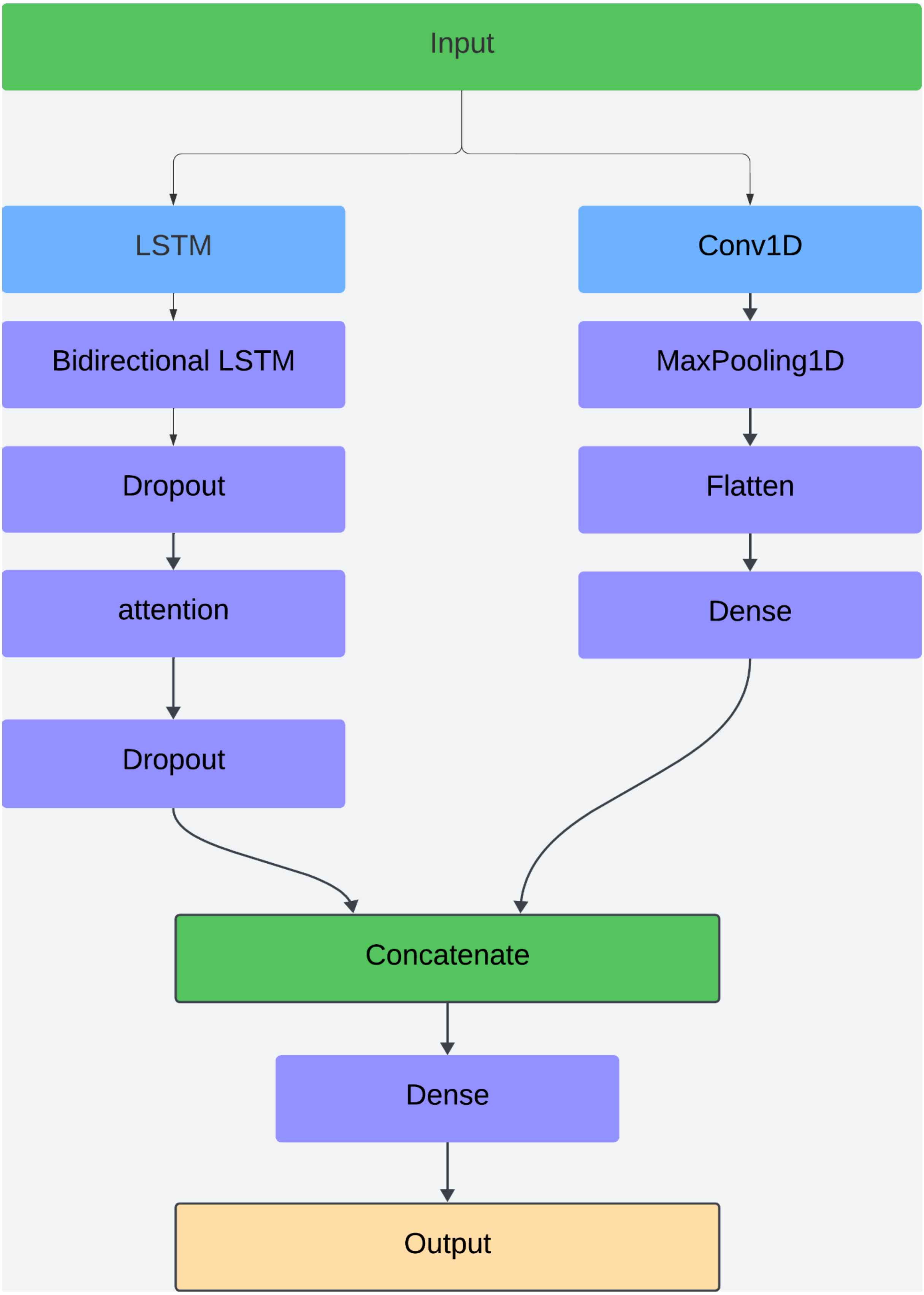

Figure 9. Architecture of the suggested Bi-LSTM attentional Temporal Convolutional Neural Network(TCNN)

Conclusion

In this chapter, the proposed method was fully described. At first, the working method of the proposed method and then the working methodology were determined. Next, the teaching method and methodology steps were examined one by one. Next, the architecture of the neural network and the attention mechanism used to increase the accuracy of the proposed model were described. Finally, the architecture of the neural network and the structure of its layers were drawn. In the next chapter, we will evaluate the proposed method to determine its effectiveness for us.

RESULTS AND DISCUSSION

In this chapter, we evaluate the proposed solution. First, we will verify the system required for testing. Next, we will describe the methods used for comparison with the proposed method. Following that, we will introduce the metrics needed to evaluate the efficiency of the different methods. Finally, we will implement various experiments to evaluate and compare the methods, report the results, and draw general conclusions from the evaluation.

Two codes will be run: one using the entire dataset, and the second using balanced data.

Dataset

The proposed approach has been assessed utilizing the Breizhcrop dataset (BreizhCrops, n.d.), which encompasses four regions labeled as Frh01, Frh02, Frh03, and Frh04, depicted in Figure 14.

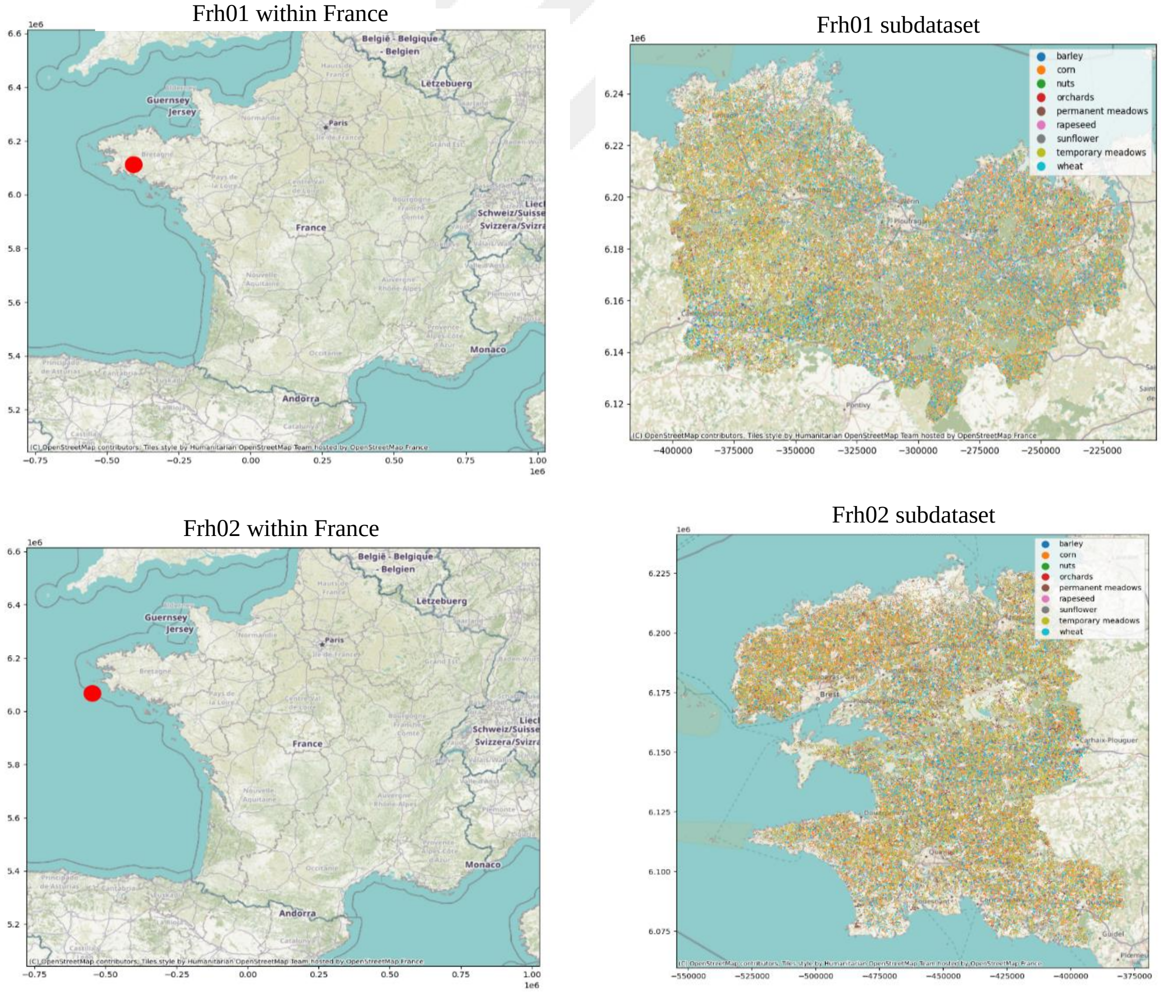

Figure 10. The regins of Breizhcrop dataset (BreizhCrops, n.d.) (more)

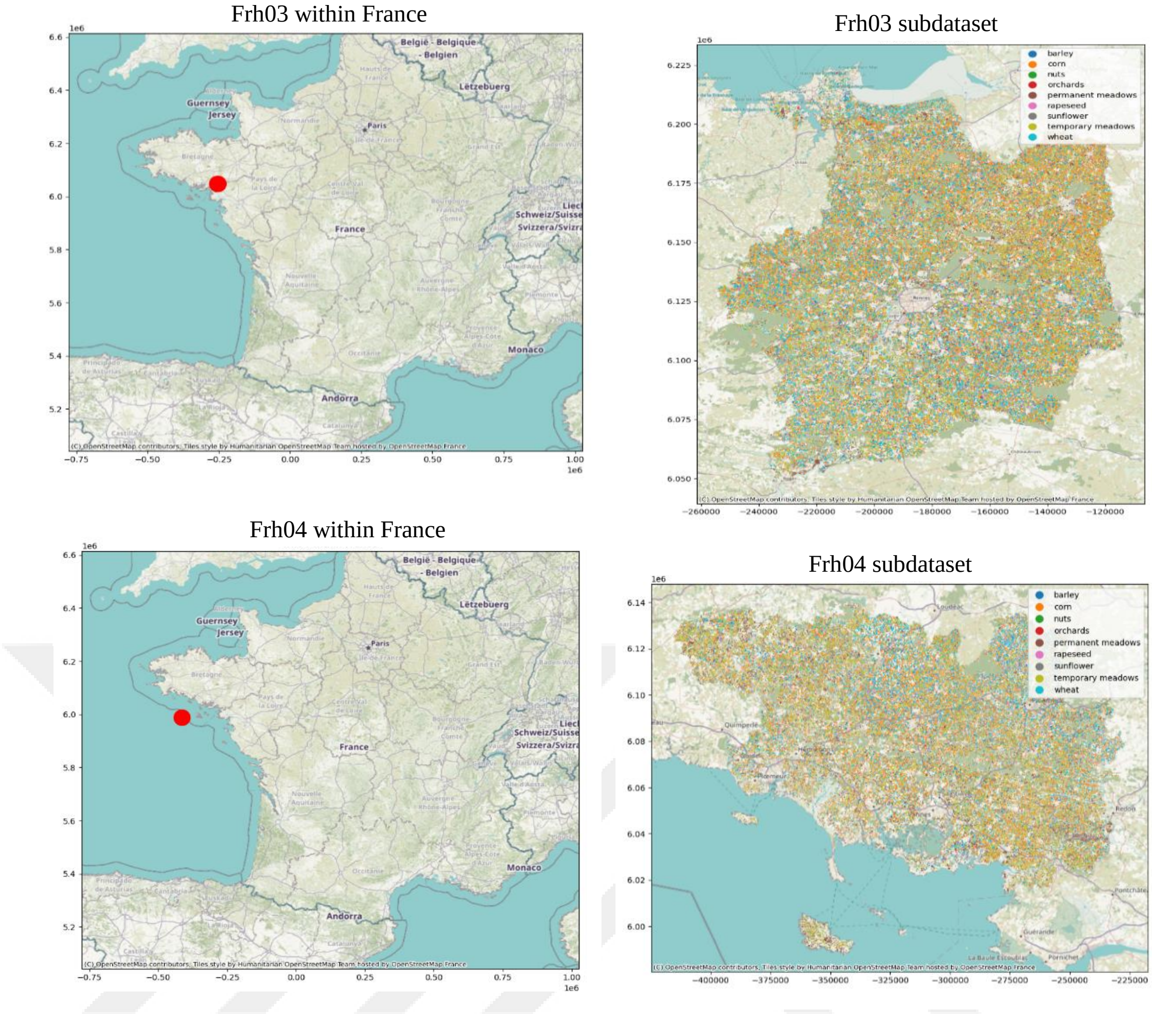

Figure 11. The regins of Breizhcrop dataset (BreizhCrops, n.d.)

Table 3 provides a comprehensive breakdown of the Breizhcrop dataset, detailing the number of data points for each region (Frh01, Frh02, Frh03, and Frh04) and each crop class within these regions. It also lists the names of the crop classes and the total number of data points in the dataset.

Tablo 3. Distribution Of Data Points Across Regions And Crop Classes İn The Breizhcrop Unbalanced 9-Class Dataset

Crop Type	Frh01	Frh02	Frh03	Frh04	Total
temporary meadows	52011	39082	52728	38391	182212
Wheat	30368	15005	27189	16993	89555
corn	43990	36593	41992	31333	153908
Permanent meadow	32650	36512	32534	26117	127813
barley	13046	10733	7148	5978	36905
rapeseed	5593	2346	3557	3236	14732
orchards	944	350	1223	553	3070
nuts	10	18	10	11	49
sunflower	1	6	10	2	19
Total	178613	140645	166391	122614	608263

A series of farms have been tracked through remote sensing data in this dataset. There are different data items with 13 classes in this dataset, and this dataset has 13 features. The dataset includes 13 spectral bands from the Sentinel-2 satellite, specifically B1 through B12 and an additional band B8A. These features cover a range of wavelengths from the visible to shortwave infrared spectrum, providing comprehensive data for various applications such as vegetation monitoring, land use classification, and water quality assessment (Sentinel-2 UH, 2024).

Figure 15a illustrates an example of data from the dataset, depicting a field where corn was planted in 2017. This information can be visualized on a map as shown in Figure 15b.

Despite the dataset having 13 crop classes, only 9 classes are present in the main dataset, as detailed in Table 2. This table also shows how the data is distributed across different regions and the number of fields planted with each crop class in each region.

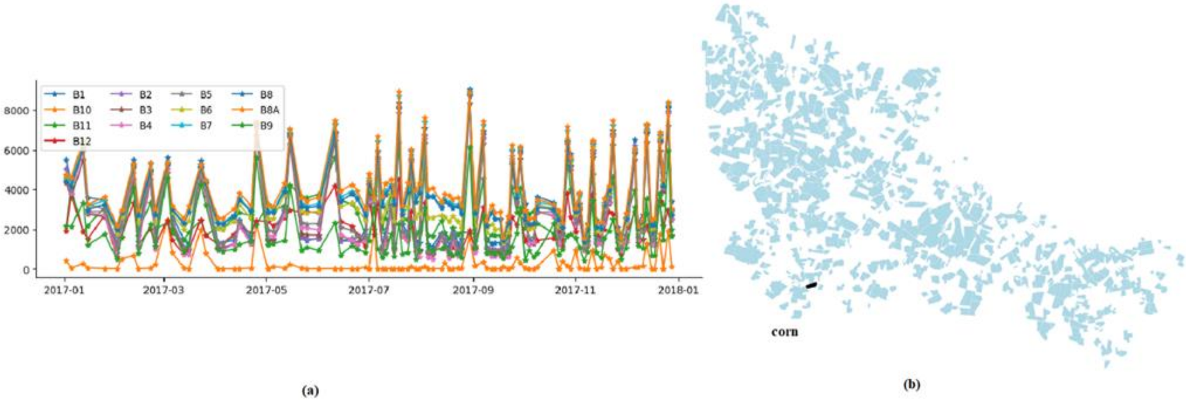

Figure 12. (a) Data of emitted bands in remote sensing images over time (b) The field sample from the dataset where corn is planted (BreizhCrops, n.d.)

To ensure the data could be evaluated and balanced, we removed two classes with a small number of instances and no specific product categories. For the remaining seven classes, undersampling was applied to achieve balance. Table 4 and Table 5 displays the balanced dataset used for evaluation. In total, 21490 data points will be utilized for training and evaluating the proposed model.

Tablo 4. Balanced 7-Class Dataset Used For Evaluation

Crop Type	Total	Train Set	Test Set
temporary meadows	3070	2456	614
Wheat	3070	2456	614
Corn	3070	2456	614
Permanent meadow	3070	2456	614
Barley	3070	2456	614
Rapeseed	3070	2456	614
Orchards	3070	2456	614
Total	21490	17192	4298

Tablo 5. Distribution of Crop Types Across Different Regions For Balanced 7-Class Dataset

Crop Type	Frh01	Frh02	Frh03	Frh04	Total
temporary meadows	768	767	767	768	3070
Wheat	768	767	767	768	3070
corn	768	767	767	768	3070
Permanent meadow	768	767	767	768	3070
barley	768	767	767	768	3070
rapeseed	768	767	767	768	3070
orchards	944	350	1223	553	3070
Total	5552	4952	5825	5141	21490

Evaluation Metrics

Common metrics for assessing the effectiveness of classification models include recall, precision, and F1 scores. These metrics not only reveal the model's ability to classify instances correctly but also provide insights into the accuracy of the classification. Furthermore, in cases where the dataset's class distribution is imbalanced, the Kappa score is used to measure the level of agreement between the predicted and true labels (Rußwurm & Korner, 2017).

- **Precision** measures the proportion of correctly predicted positive instances out of all instances predicted as positive. It evaluates the model's accuracy in identifying true positives while minimizing false positives. Precision is calculated as follows:

$$\textbf{Precision} = \frac{TP}{TP+FP}$$

- **Recall**, also known as the true positive rate or sensitivity, is the percentage of actual positive instances that are correctly identified by the model. It assesses the model's ability to detect all positive instances without missing any. Recall is calculated as follows:

$$\textbf{Recall} = \frac{TP}{TP+FN}$$

- **F1 Score** is a combined metric that considers both precision and recall. It represents the harmonic mean of precision and recall, providing a balanced measure of the model's performance. The F1 score is calculated as follows:

$$\textbf{F1 Score} = \frac{2*Precision*Recall}{Precision+Recall}$$

F1 scores range from 0 to 1, with 1 representing the signifies the optimal performance.

- In statistical analysis, the Kappa score, also known as Cohen's kappa coefficient, gauges the agreement between predicted and true labels while considering the potential for chance agreement. It is particularly useful when dealing with unbalanced datasets, where accuracy alone may be deceptive. Scores closer to 1 suggest a higher level of agreement than would be expected by chance, scores closer to 0 indicate agreement at chance levels, and negative scores signify poorer agreement than would be expected by chance. The Kappa score is computed based on both the observed agreement (the number of correctly predicted events) and the expected agreement (the number of events predicted by chance). The formula for the Kappa score is as follows:

$$\textbf{Kappa} = \frac{\text{Observed Agreement} - \text{Expected Agreement}}{1 - Expected\ Agreement}$$

In this computation, we operate under the assumption that the predicted labels and actual labels are distributed randomly. Various evaluation metrics offer valuable insights into the model's performance, and the selection depends on the particular demands of the problem at hand. Precision holds greater significance in situations where false positives are critical, while recall is prioritized in instances of false negatives. Assessing agreement beyond chance often calls for the F1 score, especially in the context of imbalanced datasets where the Kappa score proves particularly useful.

Setup used for evaluation

To carry out the simulation and experiments in the research as well as the programming done during the research in a system with the following hardware specifications:

Processor: core i7 8550U 4.00GH

Memory: 12 GB

Graphics: Nvidia GeForce 930MX

And Windows 10 operating system has been used as the operating environment. Python programming language has also been used in all stages. On the other hand, all figures and graphs as well as related statistical analyzes have been done using the Jupyter and Spyder programming environment.

Methods and Parameters Setting

This section applies three models—temporal CNN, vanilla LSTM, and star RNN—to validate the effectiveness of the neural network discussed in the preceding section. These methods have been widely employed in numerous studies for crop classification using remote sensing data. The evaluation of the proposed methodology utilizes the Breizhcrop dataset, with various classification metrics employed for method comparison. Across all iterations, classification outcomes are assessed based on F1 score, Cohen's kappa score (κ), recall, and precision. Below is a brief overview of each model.

1. **Temporal CNN (TCN)** (Zhu *et al.* 2020): The Temporal Convolutional Neural Network (TCN) is a framework designed for sequential data modeling, such as time series and natural language processing. TCNs leverage the structure of convolutional neural networks (CNNs) to handle input sequences. Unlike traditional recurrent neural networks (RNNs) like LSTMs or GRUs, TCNs are particularly effective at capturing long-term dependencies in sequential data. Additionally, TCNs offer faster processing speeds and greater memory efficiency compared to RNNs, as they can process input sequences in parallel.
2. **Star RNN** (Cheng *et al.* 2020): Many models for sequential data are based on recurrent neural networks (RNNs). RNNs, like feedforward networks, stack multiple recurrent layers to derive higher-level abstractions from the data. However, stacking too many recurrent layers can lead to performance issues such as exploding or vanishing gradients during training, limiting the effectiveness of the network. To overcome this challenge, Star cells are introduced, allowing the development of much deeper recurrent architectures. RNNs that incorporate Star

cells are known as Star RNNs, providing a solution to the limitations of traditional RNNs by enabling the creation of significantly deeper models.

3. **Vanilla LSTM** (Li *et al.* 2019): A vanilla LSTM is the simplest form of the Long Short-Term Memory (LSTM) architecture, featuring three key gates: input, output, and forget. These gates control the flow of information within the network's internal memory, known as the cell state. The input gate determines what new information is added to the cell state, the forget gate decides what information is discarded, and the output gate manages what information is output from the cell. Vanilla LSTM can handle input sequences of varying lengths and is effective at capturing long-term dependencies in sequential data. It is commonly used in applications such as speech recognition, machine translation, and video analysis. While Vanilla LSTM is powerful for modeling sequential data, it can be difficult to train and requires careful tuning of hyperparameters. Variants like gated recurrent units (GRU) and peephole LSTMs add extra gates and modifications to the cell state update formula to enhance performance. LSTMs are specifically designed to address the vanishing gradient problem and effectively capture long-term dependencies in sequential data.

In Table 6, we have shown various parameters used in neural network training. The number of repetitions of the neural network is equal to 50, and the input categories to the network are processed in batches of 64. On the other hand, the probability of activation of dropout layer neurons is considered equal to 0.2, and 80% of the total data is used for training while 20% of it is used for evaluating the model.

Tablo 6. Neural Network Parameters and Value of Each Parameter

Parameter	Value
Epochs	50
Dropout Layer Probablity	0.2
Batch Size	64
Training Set Percentage	80
Test Set Percentage	20

Table 7 decribes the parameters and layers of different methods used in this thesis.

Tablo 7. Parameters and Layers For Different Methods

Model	Parameter and layers	Description
Temporal CNN	Kernel Size	The kernel size denotes the width × height dimensions of the filter mask.
	Conv1D Layer	This layer generates a convolution kernel which is convolved with the layer input across a single spatial (or temporal) dimension, resulting in a tensor of outputs.
Star RNN	Learning Rate	The learning rate serves as a tuning parameter within an optimization algorithm, dictating the step size at each iteration while progressing towards minimizing a loss function.
	Star Layer	The stackable recurrent (STAR) cell enables significantly deeper recurrent architectures.
Vanilla LSTM	Number of sequence	The number of memory cells for the sequence of data input to the model.
	LSTM layer	An LSTM layer represents a recurrent neural network (RNN) layer designed to capture long-term dependencies among time steps within time-series and sequence data.
Bi-LSTM Attentional temporal CNN	Concatator	It yields a unified tensor resulting from the concatenation of all input features.
	BI-LSTM layer	The BI-LSTM layer is a recurrent neural network (RNN) layer that adeptly learns bidirectional long-term dependencies within time-series or sequence data.

Classification Performance

In this section, the model was trained using 80% of the dataset, while the remaining 20% was utilized for validation. The proposed neural network architecture was compared with existing methods, and the results are presented in Table 8. The table shows the classification performance across different methods, highlighting the number of classes, number of data points, model parameter count, training time, validation loss, and validation accuracy.

According to the findings, the proposed neural network outperformed existing methods across multiple classification evaluation metrics. Specifically, the LSTM network exhibited suboptimal performance when used alone, but incorporating attention significantly improved its accuracy. Similarly, while the Temporal-CNN network performed well independently, its efficiency was further enhanced with the addition of the proposed attention layer.

Tablo 8. Classification Evaluation Reports for Different Methods

	Method	Number of Classes	Number of Data Points	Model Parameter Count	Training Time (seconds)	Validation Loss	Validation Accuracy
BALANCED 7-CLASS DATASET	BI-LSTM	7	21490	240,679	3451	0.07	0.86
	Temporal CNN	7	21490	321,399	626	0.44	0.84
	Vanilla LSTM	7	21490	125,767	2729	0.48	0.85
	Simple RNN	7	21490	3,707	12500	0.58	0.77
UNBALANCED 9-CLASS DATASET	BI-LSTM	9	608263	240,781	39099	0.48	0.82
	Temporal CNN	9	608263	321,601	8109	0.49	0.79
	Vanilla LSTM	9	608263	125,833	49658	0.40	0.81
	Simple RNN	9	608263	3,809	16650	0.60	0.51

Figure 16 illustrates the confusion matrix for all four tested neural networks. This matrix presents the percentage of correct detections for each class along its diagonal. Results indicate that the proposed method achieves the highest accuracy across all classes (Figure 16d), followed by the LSTM and Temporal-CNN methods (Figure 16a, Figure 16b), which demonstrate superior performance for specific classes. The Star-RNN method (Figure 16c) exhibits good accuracy for all classes, albeit slightly lower than that of the proposed method.

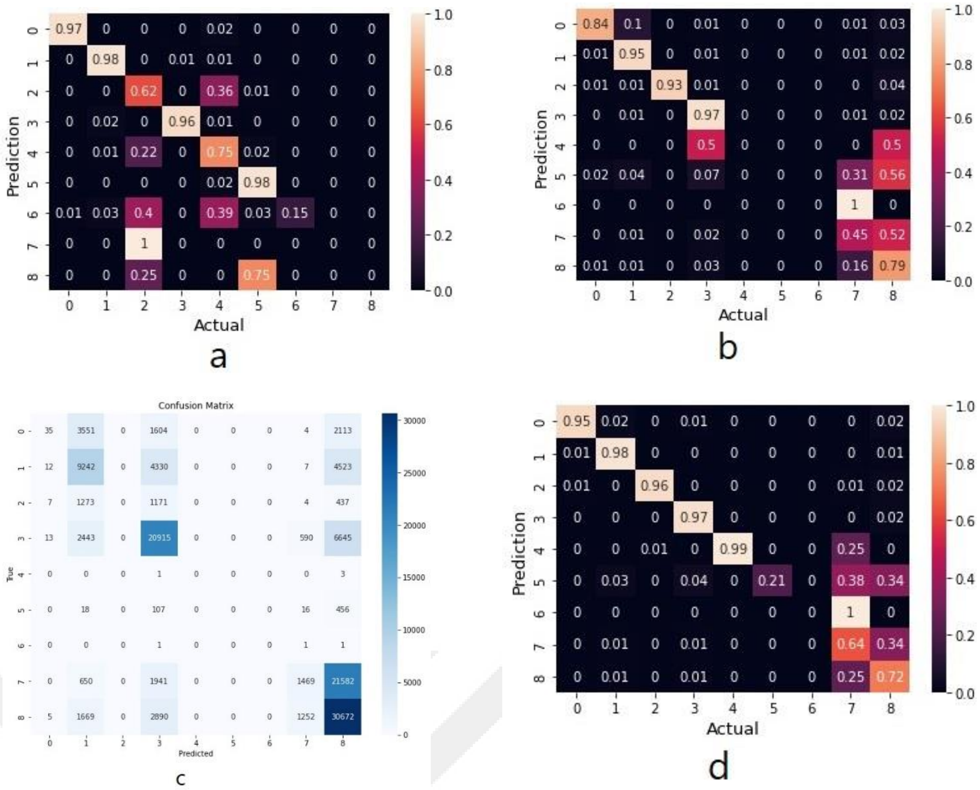

Figure 13. Confusion matrix for (a) Vanilla LSTM (b) Temporal Convolutional Neural Network (TCNN) (c) Star RNN (d) Bi-LSTM Attentional temporal CNN

In Table 9, we present a comparison between recent related works focusing on time series image data and our proposed method in terms of accuracy and efficiency. Our proposed method exhibits approximately 0.17 higher accuracy compared to other existing methods. Notably, approaches such as Triplet-LSTM, employing three consecutive LSTM layers for feature extraction, or the transformers method utilizing an Encode and Decode mechanism, have demonstrated commendable performance. Meanwhile, the Vanilla LSTM method, previously employed on this dataset, yielded results indicating superior performance of our proposed method over others. All these methods emphasize feature extraction, and our approach consistently outperforms them in this aspect both presently and over time.

Our proposed method achieved an accuracy of 86% for the balanced 7-class dataset, while it achieved 82% for the unbalanced 9-class dataset.

In next step other research result has been compared with our proposed method.

Tablo 9. Different Methods Classification Evaluation Reports

Author	Type of Corps	Methodology	Accuracy
Teloğlu & Aptoula (2022)	Barley, Wheat, Rapeseed, Corn, Misc., Permanent meadow, Temporary meadow	(SSLSTM-AE)	0.75
Bozo *et al.* (2020)	Barley, Rapeseed, Misc., Wheat, Permanent meadow, Corn, Temporary meadow	TripletLSTM	0.642
Rußwurm *et al.* (2023)	Wheat, Misc, Fodder, Barley, Corn, Orchards, Cereals, Fallow, Perm. Meadows, Rapeseed, Temp. Meadows, Vegetables, Protein crops.	Vanilla-LSTM	0.63
Proposed Method 1 balanced 7-class dataset	Wheat, Barley, orchards, Permanent meadow, Corn, Temporary meadow, Rapeseed	Bi-LSTM Attentional temporal CNN	0.86
Proposed Method 2 unbalanced 9-class dataset	Wheat, Barley, orchards , sunflower,Nuts, Permanent meadow, Corn, Temporary meadow, Rapeseed	Bi-LSTM Attentional temporal CNN	0.82

CONCLUSION

In the realm of machine learning, classifying crops based on time series data derived from remote sensing data poses significant challenges. Numerous efforts have been dedicated to enhancing neural networks for this purpose. This research aimed to enhance network training by leveraging an attention mechanism on the LSTM layer to capture effective temporal features. Additionally, features of the time series data were extracted using a temporal CNN neural network, which was integrated with the aforementioned approach to boost network efficiency. Incorporating a bidirectional layer further refined the construction of the attention layer, allowing for data traversal from both the beginning to the end and vice versa, thereby enhancing neural network accuracy.

Based on experimentation with the Breizhcrop dataset, the neural network demonstrated greater efficiency across metrics such as Kappa, recall, precision, and F1 score. Specifically, the model achieved an accuracy of 82% when using the entire dataset and an improved accuracy of 86% when the data were balanced according to class counts. Alternatively, the optimal training speed and number of network parameters indicate their balance with the accuracy obtained from validation.

One significant limitation of this model is its requirement for each time series to contain a minimum amount of data. A potential avenue for improvement could involve developing a new model that circumvents this limitation. Another constraint of the proposed method relates to its reliance on additional features, such as indices like NDVI, which could potentially enhance model accuracy by incorporating new indices derived from diverse spectral data sources. Furthermore, a limitation arises from the necessity for data to possess similar time series characteristics, which may not always be feasible due to data availability constraints in certain regions. Moreover, achieving high accuracy with this model necessitates the availability of several long-term time series, although alternative models exist that can attain comparable accuracy with fewer series.

Future research could explore the impact of employing different attention mechanisms, potentially yielding greater improvements than variations in data types. Additionally, exploring the utilization of different deep neural network models for processing time series data could provide valuable insights. Lastly, proposing effective dataset balancing methods tailored to this data type remains crucial for further advancements in this field.

Recommendation for Further Works

Based on the research conducted, we have listed some suggestions for future research that the researchers encountered in the process of this research as follows:

- In future research, other attention mechanisms can be used and their efficiency can be investigated. In this research, the attention mechanism was implemented using the temporal CNN method. However, there are other methods such as zero shot or transformers that can detect these areas with high accuracy. On the other hand, other side features can be used to check the neural network.
- Different methods can be considered for data balancing to check the effect of the methods on the quality of model training. Many patterns have been used to balance the data. Among these methods, we can mention data augmentation using clustering techniques.
- Our method showed promising results on the BreizhCrops dataset. However, since this study was conducted on a single dataset, generalizations about its performance on BreizhCrops cannot be made. Therefore, in future works, it is planned to apply this method to other datasets to validate its effectiveness and generalizability.

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RESUME

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